

Masters Program in **Geospatial Technologies**



ANALYSIS OF URBAN LAND USE AND LAND COVER CHANGES:

A Case Study in Bahir Dar, Ethiopia

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***ANALYSIS OF URBAN LAND USE AND LAND COVER CHANGES:
A Case Study in Bahir Dar, Ethiopia***

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ABSTRACT

The high rate of urbanization coupled with population growth has caused changes in land use and land cover in Bahir Dar, Ethiopia. Therefore, understanding and quantifying the spatio-temporal dynamics of urban land use and land cover changes and its driving factors is essential to put forward the right policies and monitoring mechanisms on urban growth for decision making. Thus, the objective of this study was to analyze land use and land cover changes in Bahir Dar area, Ethiopia by applying geospatial and land use change modeling tools. In order to achieve this, satellite data of Landsat TM for 1986 and ETM for 2001 and 2010 have been obtained and preprocessed using ArcGIS. The Maximum Likelihood Algorithm of Supervised Classification has been used to generate land use and land cover maps. For the accuracy of classified land use and land cover maps, a confusion matrix was used to derive overall accuracy and results were above the minimum and acceptable threshold level. The generated land cover maps have been run with Land Change Modeler for quantifying land use and land cover changes, to examine land use transitions between land cover classes, to identify gain and losses of built up areas in relation to other land cover classes and to assess spatial trend of built up areas. Finally, Land Change Modeler has been run to model land use and land cover changes in Bahir Dar area and to predict future urban land use changes. To achieve this, four model variables that explain urban growth and six land cover transitions were incorporated in the modeling process. Multi-layer perceptron neural network was used to model the transition potential maps and achieved an accuracy of 61%. This result was acceptable to make actual prediction using Markov chain analysis for year 2010. Validation results showed that the model (Land Change Modeler) had a lower accuracy in simulating changes for the year 2010. Generally, the results of this study have shown that there was an increased expansion of built up areas in the last 25 years from 1.5% in 1986 to 4.1 % in 2001 and 9.4% in 2010 at the expense of agricultural areas. The spatial trend of built up areas also showed that there was a growing trend in the western part of Bahir Dar relative to other directions. Therefore, the findings of this study could provide as decision making for urban planning.

KEYWORDS

Bahir Dar

Change detection

Geographical Information system

Image classification

Land Change Modeler

Land use and land cover change

Remote sensing

ACRONYMS

ANRS - Amhara National Regional State

ANN - Artificial Neural Network

CA - Cellular Automata

CORINE- Co-ordination of Information on the Environment

CSA - Central Statistical Agency

DEM - Digital Elevation Model

EEA - European Environment Agency

ETM- Enhanced Thematic Mapper

GIS - Geographical Information System

GLCF - Global Land Cover Facility

IGBP - International Geosphere and Biosphere Programme

IHDP - International Human Dimensions Programme

LCM - Land Change Modeler

MCE - Multi Criteria Evaluation

MLP - Multi Layer Perceptron

OIES - Office of Interdisciplinary Earth Studies

REDD - Reducing Emissions from Deforestation and Forest Degradation

SSA - Sub-Saharan African

SSE - Supervised Spatial Encoder

UNFPA - United Nations Population Fund

USGS - United States Geological Survey

WGS -World Geodetic System

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CHAPTER ONE

1. INTRODUCTION

1.1. Background of the Study

Rapid urbanization has been the main theme of urban studies in developing countries since the explosion of rates of growth in the 1960's and 1970's in very large cities (Barros, 2004). Like other anthropogenic-environment interactions, urban land cover changes respond to socioeconomic, political, cultural, demographic and environmental conditions, largely characterized by a concentration of humans (Masek et al, 2000). In spite of its small area coverage relative to the earth's surface, dynamic urban growth processes, particularly the expansion of urban population in a larger extent and urbanized area, have a significant impact on natural and human environment at all geographic scales (Herold et al, 2005).

According to the United Nations report on World Urbanization Prospects, the world urban population is expected to increase by 72 % by 2050, from 3.6 billion in 2011 to 6.3 billion in 2050. Thus, the urban areas of the world are expected to absorb all the population growth expected over the next four decades while at the same time people are moving to rural areas by assuming that rural life is seen as simpler and less stressful. Furthermore, in the cities and towns of less developed regions the expected population growth is more concentrated than the developed regions of Europe and America (Desa, 2012).

Associated with the rapid expansion of urbanization, a lot of land has been converted from rural to urban. From the land use and land cover change point of view, expansion of urban areas is of greater importance because of its strong effect on other land cover classes, such as agricultural lands, non built areas, forests and others. Ethiopia, having the second largest population in Africa has a total of over 80 million population. It has a 2.3% of annual growth rate and having 4.6% average annual urban growth rate (Haregeweyn et al, 2012). In spite of its low urbanization rate compared to other African countries, the impact of land

use and land cover changes become a big challenge to the country. Bahir Dar is a region in Ethiopia, where this study conducted, has also experienced greater changes. Analyzing and modeling these changes, therefore, provide a better information for urban planners and decision makers to design strategies and solutions to manage the impacts of land use and land cover changes in both spatial and temporal scales.

Understanding the rapid growth dynamics, developments of urban sprawl and quantifying the spatial extent of urbanization requires a geospatial tool (Araya and Cabral, 2010). Since accurate and timely information of land use and land cover change is highly necessary to many groups, remotely sensed data can be used as it provides the land cover information. It is also important for estimating levels and rates of deforestation, habitat fragmentation, urbanization, wetland and soil degradation and many other landscape-level phenomena (Vogelmann et al, 2001). The main focus of this study is, therefore, detecting and analyzing land use and land cover changes in Bahir Dar area by integrating remote sensing, Geographical Information System (GIS) and spatial modeling tools.

1.2. Statement of the Problem

Land as a finite and a potentially productive natural resource represents our basic food production facility. However, the diversity of residents and intensive use of the resources through the increasing of population coupled with economic activities and global market drive unprecedented land use and land cover changes (Ezeaku and Davidson, 1992). These changes lead to transformations in the hydrological, ecological, geomorphologic and socioeconomic systems and which are often neglected by both rural and urban administrations. Thus, special attention and continuous assessment are required for monitoring and planning urban development and decision making.

Bahir Dar city is perceived as a place where one could have a better life; because of better opportunities, higher salaries, better services, and better lifestyles. It is also considered as one of the most beautiful, well planned, and safest cities by many standards, and in 2002 it was awarded the UNESCO Cities for Peace Prize for addressing the challenges of rapid

urbanization (Wikipedia, 2013). As a result an influx of people is moving from rural areas. This would have significant impact on the surrounding ecosystem: loss of agricultural land, destruction of forest cover, water depletion and on the benefits generated from the land. Because of this rapid growth on the urban-rural fringe, planners and policy makers lack accurate, timely and cost effective urban land use data which is most essential to make decision concerning land resource management. Quantifying changes in land use and land cover and modeling of it for future time is, therefore, important in Bahir Dar, Ethiopia for monitoring and resolving the negative consequences. This could be useful for better land use management and environmental development in the study area.

1.3. Objective of the Study

The main objective of this study was to detect and analyze land use and land cover changes in Bahir Dar area by integrating remote sensing techniques and Land Change Modeler. The specific objectives of this study were:

- To produce land use and land cover maps of the study area for selected times;
- To analyze the dynamics of urban land use changes within the selected times;
- To evaluate the accuracy assessment of the classification techniques;
- To quantify gain and losses of land cover classes, examine land use transitions and asses spatial trends of changes in built up areas using Land Change Modeler;
- To evaluate the predictive power of the Land Change Modeler in simulating and predicting of urban land use in Bahir Dar;
- To recommend possible mitigation measures to minimize the effects of land use changes.

1.4. Research Questions

As this study mainly focuses on built up areas, the following research questions were set:

- Were there any major changes in the built up areas within the study periods?
- How was the spatial trend of changes (growth) of the built up areas during the study periods?
- How was the contribution of land cover classes for the growth of built up areas?
- Had the model been satisfactory in predicting and simulating the changes?

1.5. Significance of the Study

Land use and land cover change is a major aspect of the pressure on the limited land resources that is driven by different biophysical and anthropogenic factors particularly population growth. Therefore, analyzing and modeling of urban land use changes provide greater importance to the research community, urban planners, stake holders as well as decision making groups in terms of understanding the impacts of land use land cover changes in Bahir Dar area.

The results of this study could provide better information about the changes in urban land use quantified through integrated application of GIS, remote sensing and land change modeler. In addition, it also provide the opportunity to understand the trends of changes in built up areas as a result of driving variables. Moreover, the findings of this study will be an initial input for future research direction for interested groups in the area.

1.6. Structure of the Thesis

The first chapter introduces statement of the problem and introduction, study objectives, research questions and significance of the study. The next section, chapter two, concentrates on theoretical literature review and related work for this study. This section presents brief understanding of land use and land cover changes, land use change models, the use of remote sensing in land use and land cover change, image classification, change detection methods and accuracy assessments of land cover maps generated in the

classification. The third chapter focuses on the general methodology followed, the data sets used in this study and detail explanation of the study area. This chapter highlights all the procedures and techniques applied for image classification and land use modeling including the tools such as ArcGIS and Land Change Modeler. The results and discussions is the fourth chapter which presents the quantified results from image classification and land use change modeling. In this section, land cover maps generated using maximum likelihood classification, change detection and accuracy assessments of the classification are discussed in detail. Moreover, change analysis using Land Change Modeler, spatial trends and simulation of land cover maps has been performed. Validation of the simulated land cover maps has been done for comparison of model performance. The last chapter presents conclusions and recommendations. In this section, key findings and critical points that need further treatment has been forwarded as a recommendation for future work.

CHAPTER TWO

2. LITERATURE REVIEW

The earth's surface has been changed considerably over the past decades by humans because of urbanization, deforestation and agriculture. Even though the conversion of land to agriculture and deforestation rates vary across the world, the number of people residing in cities has been increasing continuously. Urbanization has been increasing since World War II, and has not shown any sign of decline and is likely to continue into the twenty-first century (Oğuz, 2004). In this chapter, previous related published works are discussed in order to strengthen this specific study.

2.1. Land use and Land cover Changes

The definition of land use and land cover has been used interchangeably in the land use research community because of the availability of many existing information systems. However, these two terms explain two different issues and meanings. Land cover refers to the observed biophysical cover on the earth's surface including vegetation, bare soil, hard surfaces and water bodies. Whereas land use is the utilization of land cover type by human activities for the purpose of agriculture, forestry, settlement and pasture by altering land surface processes including biogeochemistry, hydrology and biodiversity (Di Gregorio and Jansen, 2000).

Land use and land cover changes became prominent as a research topic on the global environmental change several decades ago with the idea of processes in the earth's surface influence climate. In early 1980's the significance impact of land use and land cover change on the global climate via carbon cycle was understood where terrestrial ecosystems acted as a source and sinks due to the changes. Following this, the forthcoming volume of the 1991 Global Change Institute of the Office of Interdisciplinary Earth Studies(OIES) dedicated to land use and land cover changes at global level by explaining the major recent trends of changes, their consequences in environment, human causes on it as well as data

and modeling of changes (Meyer and Turner, 1992). Latter, under the support of land use and land cover change project of the International Geosphere and Biosphere Programme (IGBP) and International Human Dimensions Programme on Global Environmental Change (IHDP), the research community has identified three basic issues. These were understanding the causes of land use and land cover changes, how to quantify it and how to apply models of predicting the changes (Lambin et al, 2003).

Conversion and modification are the two forms of land cover changes described by Meyer and turner (1992) where the former is a change from one class of land cover to another (e.g from grassland to cropland). The latter is, however, a change within a land cover category (e.g thinning of a forest or a change in composition). Land cover changes due to human activities drive land use and hence a single class of cover could support multiple uses (forest used for combinations of timbering, slash and burn agriculture, fuel wood collection and soil protection). On the other hand, a single system of land use can maintain several covers (as certain farming systems combine cultivated land, improved pasture and settlements).

Changes in land use and land cover caused through direct and indirect consequences of human activities on the environment for the purpose of having better life. One of the direct impact of humans is population growth where its increase and decrease have effects on land use especially in developing world at longer time scales. According to Lambin et al (2003), it can also be caused by the mutual interactions between environmental and social factors at different spatial and temporal scales as land use and land cover change is a complex process.

Verburg et al (2002) showed that causes of land use and land cover change can be categorized as direct (proximate) or indirect (underlying). The direct causes comprise human activities that could arise from the continuous use of land and directly alter land cover which reflect that human are driving forces. They are generally operated at local levels and explain how and why local land cover and ecosystem processes are modified directly by humans. On the other hand, indirect causes are fundamental forces that

strengthen the more direct causes of land cover changes. These causes are resulted due to the complex interaction of social, political, economic, technological and biophysical variables.

Land use and land cover changes have significant consequences on climate change, hydrology, air pollution and biodiversity. Meyer and Turner (1992) mentioned in their study that it caused a various microclimatic changes. The rise in global surface temperature is associated with deforestation through changes in land use. This in turn caused a strong warming in urban environment called urban heat island. Their study also showed water pollution occurred due to land cover changes from cultivation to settlement (urban areas). It has been reported also that loss of forest species has wide range of effects on biodiversity.

Identifying the causes and impacts of land use and land cover change require understanding both how people make land-use decisions and how specific environmental and social factors interact to influence these decisions (Lambin et al, 2001). In order to understand the impacts of dynamic land use and land cover changes, the use of land use change models become an advantage since they provide information of land use trajectories by projecting for the future. This ability of models, however, important for better environmental management and land use planning (Verburg et al, 2002).

2.2. Urban Land use Changes

From a broader point of view urbanization is one of the ways in which human activities altering global land cover. Although urbanization trend is global, according to the reports of the United Nations Centre for Human Settlements (Habitat, 2001), it has showed most remarked changes in developing countries associated with the migration of rural people to cities for better opportunities. Following this there had been estimated a rapid growth of population in urban areas at an average rate of 2.3% per year between 2000-2030 (Nations, 2001).

Urban growth, particularly the movement of residential and commercial land use to rural areas at the periphery of metropolitan areas, has long been considered as a sign of regional economic vitality (Yuan et al, 2005). However, its importance become unbalanced with impacts on ecosystem, greater economic differences and social fragmentation. It can be defined as the rate of increase in urban population. Dynamic processes due to urban change, especially the tremendous worldwide expansion of urban population and urbanized area, affect both human and natural systems at all geographic scales (Brockerhoff, 2000).

Araya and Cabral (2010) have shown that urban growth in Setúbal and Sesimbra, Portugal has been increased significantly between 1990 and 2000 by 91.11%. Much of this growth, however, was towards the periphery of urban areas due to the coalescence of a number of smaller settlements as well as through the consumption of agricultural land. The growth was predicted to continue in the future and would have wide range of consequences on natural resources. Their study also noted that population growth was one of the major driving factor for such rapid growth in the study area.

Traditionally demographic data has been used to asses urban sprawl (Carlson and Traci, 2000). Meanwhile the use of aerial photography become important to update land cover maps. Since land cover changes at regional level occurred increasingly due to human activity, the changes couldn't be realized in the community. Therefore, accurate and updated information is required to design strategies for sustainable development and to improve the livelihood of cities.

The ability to monitor urban land cover and land use changes is highly desirable by local communities and policy decision makers. Due to the increased availability and improved quality of multi spatio-temporal data and new analytical techniques, nowadays it is possible to monitor urban land cover and land use changes and urban sprawl in a timely and cost-effective way (Yang et al, 2003). Therefore, the use of satellite data provides for regional planning and urban ecology.

2.3. Trends of Urban Growth

The world is undergoing the largest wave of urban growth in history. According to the United Nations Population Fund (UNFPA, 2013), rapid population growth has been concentrated in towns and cities of the world. The report also projected that by the year 2030 the vast majority of this growth will be observed in the developing world of Africa and Asia where urban growth is highly concentrated. Because cities offer a lot of opportunities such as jobs and sources of income than the corresponding rural areas, they attracted a lot of people.

Following the rapid increase of population in urban areas, the growth of the world's rural population has shown a slowly decreasing pattern as indicated in figure 2.1 below.

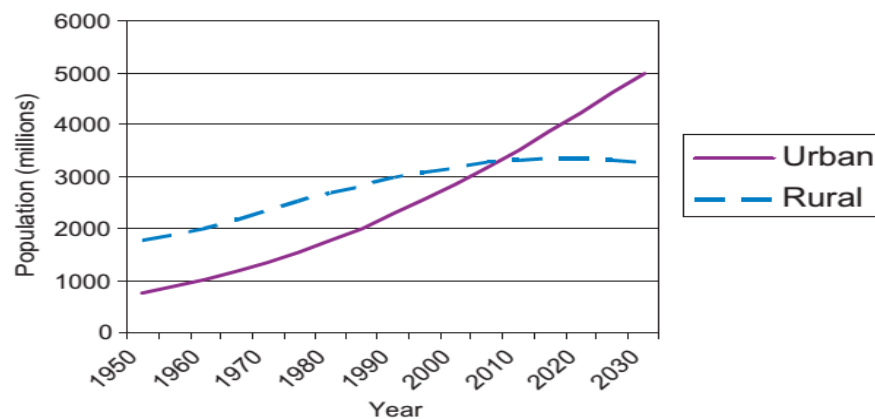


Figure 2.1: World's urban and rural population size estimated and projected, 1950–2030, (Source: Cohen, 2006).

It is clearly shown in figure 2.1 that when the world's urban population increased four-fold between 1950 and 2003, the world's rural population less than doubled going from 1.8 billion in 1950 to 3.2 billion in 2000 (Cohen, 2006). Regarding to projection of population growth, the world's urban population is expected to increase by almost 2 billion over the next 30 years, whereas the world's rural population is actually expected to decline slightly falling from 3.3 billion in 2003 to 3.2 billion in 2030.

Ethiopia is one of the second largest populated country in Africa with a total population of over 80 million and having an annual growth rate of 3.02%. The country is experiencing an average annual urban growth rate of 4.6%, which is a high rate by world standard (Cohen, 2004). Even though urbanization rates differ depending on the methodologies applied, Ethiopia's urbanization is low relative to other Sub-Saharan African (SSA) countries. Since the majority of the population (85%) is living in the rural areas, where agriculture is the backbone of the country's economy, it is evident that urban growth to be low. The self-sufficiency of agriculture also contributed to reinforcing of the rural peasant life from their territory. According to Central Statistical Agency of Ethiopia (CSA), it is only 16% of the population lived in urban areas. Among these are in small cities and towns (Schmidt and Kedir, 2011).

The city of Bahir Dar, where this study is conducted, is located in the north-western part of Ethiopia. It is one of the fastest growing city in the country. The urban area is believed to be in a dynamic state of expansion following the nomination of the city as the capital of Awraja, an administrative unit or hierarchy next to a region used during the previous regimes, in 1948. Following the fall of the former government of Ethiopia in 1991, Bahir Dar was selected as the seat of the regional government of the Amhara National Regional State (Haregeweyn et al, 2012).

2.4. Land use and Land cover Change Studies in Ethiopia

As 85% of the total population live in rural areas, 85% of the economy is dependent on agriculture with traditional farming (plough), the growth of urban population from time to time, with an increase of migration of rural population to cities for better life and the encouraging land lease policy to investors become important to study land use and land cover changes and its impacts in Ethiopia to design management and monitoring policies.

Researches on land use and land cover change in Ethiopia involved in different regions and disciplines depending on the availability of data and tools to perform analysis. However, most of the studies have focused on deforestation, the expansion of cultivated land to land

degradation, river catchments and watersheds, natural ecosystems and forests as well as the associated consequences. Among these: Amsalu et al (2007); Bewket and Abebe (2013); Tekle and Hedlund (2000); Zeleke and Hurni (2001) were found. While urban growth and its impacts are relatively studied in larger and megacities (a metropolitan area of more than ten million people) worldwide. Urban growth and modeling studies in cities of developing countries like, Ethiopia, were limited. However, few studies have been reported relatively such as: Haregeweyn et al (2012); Dorosh and Schmidt (2010); Zeleke and Hurni (2001); Amsalu et al (2007) and Bekalo (2009).

Zeleke and Hurni (2001) reported an expansion of cultivated land at the expense of natural forest cover between 1957 and 1982 in Dembecha area, north-western Ethiopia. The study also investigated a series trend of land degradation resulted due to the expansion of cultivated land on steep slopes at the expense of natural forests. Amsalu et al (2007) showed a significant decline in natural vegetation cover, however, there was an increase of plantation in Beressa watershed, in the central highlands of Ethiopia between 1957 and 2000. Yeshaneh et al (2013) also showed a significant decrease of natural woody vegetation of the Koga catchment since 1950 due to deforestation in spite of an increasing trend in eucalyptus tree plantations after the 1980's. Bewket and Abebe (2013) reported a reduction of natural vegetation cover, but an expansion of open grassland, cultivated areas and settlements in Gish Abay watershed, north-western Ethiopia.

Tegene (2002) reported a significant conversion of natural vegetation cover to cultivated land between 1957 and 1986 in Derekolli catchment of the South Welo Zone of Amhara Region, Ethiopia. Kindu et al (2013) investigated a significantly reduction of natural forest cover and grasslands, but an increase of croplands between 1973 and 2012 in Munessa, Shashemene landscape of the Ethiopian Highlands. A similar study by Tekle and Hedlund (2000) reported an increase of open areas and settlements as the expense of forests and shrub land between 1958 and 1986 in Kalu District, Southern Wello, Ethiopia.

The impacts of land use and land cover changes on the hydrological flow regime of the watershed have been reported in many studies. The impact is through altering the balance

between rainfall and evaporation and the runoff response. Muluneh and Arnalds (2011) reported an increment of a direct runoff Gum-Selassa and Maileba catchments annually from 1964 to 2006 in both catchments due to long-term changes of land use and land cover. A similar study reported the drying of Lake Cheleleka and the disappeared Lake Haramaya due to these long-term impacts. It was also reported by Geremew (2013) that land use and land cover changes affected the stream flow of gilgel Abbay watershed, Ethiopia. His study identified that there was an increase of stream flow by $16.26 \text{ m}^3/\text{s}$ during wet months and decreased by $5.41 \text{ m}^3/\text{s}$ from 1986 to 2001 as a consequence of conversion of cultivated land.

Land use and land cover changes in response to urban growth also reported by some studies that, an expansion of urban areas annually from 1957 to 2009 has been identified by Haregeweyn et al (2012) in the urban fringe of Bahir Dar area as a consequence of increasing population. Bekalo (2009) identified a significantly increase of urban areas from 34% in 1986 to 51% in 2000 in Addis Ababa, Ethiopia by the expense of agricultural land and vegetated areas driven by population growth. Dorosh and Schmidt (2010) also reported a significant urban growth for the last 3 decades as a result of increase in population of Ethiopian highlands. Muluneh and Arnalds (2011) cited on Haile (2004) that unsustainable growth of population contributed to environmental degradation especially in most populated areas such as in Ethiopian highlands.

From most of these studies it is evident that population pressure is one of the major drivers of land use and land cover changes through destruction of forest and vegetation cover for the purpose of agricultural and urban expansion as discussed by Zeleke and Hurni (2001) and Amsalu et al (2007). Population growth coupled with migration from rural to cities leads to further expansion of urban areas at the expense of vegetation cover which is commonly practiced in western highlands of Ethiopia according to Zeleke and Hurni (2001) study.

2.5. The Role of Remote Sensing on Land use and Land cover Changes

Maktav et al (2005) showed that traditional data collection methods such as demographic data, census and sample maps were not satisfactory for the purpose of urban land use management. Accurate information of land use and land cover change is therefore highly essential to many groups. To achieve this information, remotely sensed data can be used since it provides land cover information. Remote sensing refers to the science or art of acquiring information of an object or phenomena in the earth's surface without any physical contact with it. And this can be done through sensing and recording of either reflected or emitted energy and the information being processed, analyzed and applied to a given problem (Campbell, 2002).

Remote sensing is important for estimating levels and rates of deforestation, habitat fragmentation, urbanization, wetland degradation and many other landscape-level phenomena. Such useful information can be then integrated into many regional to global scale models, including those that are used to develop parameters for carbon fluxes and hydrological cycles. Therefore, remote sensing data can be used as the basis for answering important ecological questions with regional to global implications (Vogelmann et al, 2001). Herold et al (2005) also noted that one of the advantages of remote sensing is its ability to provide spatially consistent data sets covering large areas with both high detail and high temporal frequency, including historical time series.

Over the past decades almost all the remote sensing researches have given more attention to natural environment than urban areas. The reason was that urban areas have complex and heterogeneous by nature (Melesse et al, 2007). However, Herold et al (2005) reported that with the availability of high resolution imagery together with suitable techniques, urban remote sensing become a rapidly gaining interest in the remote sensing community. Supported by advanced technology and satisfying social needs, urban remote sensing has become a new field of geospatial technology and applicable in all socioeconomic environments (Melesse et al, 2007).

Following this, a number of applications of remote sensing for urban studies have shown the potential to map and monitor urban land use and infrastructure. Moreover, Herold and Menz (2001) showed urban land use information in high thematic, temporal and spatial accuracy, derived from remotely sensed data, is an important condition for decision support of city planners, economists, ecologists and resource managers. Generally, land use and land cover changes have a wide range of impacts on environmental and landscape attributes including the quality of water, land and air resources, ecosystem processes and functions (Rimal, 2011). Therefore, the use of remote sensing data and analysis techniques provide accurate, timely and detailed information for detecting and monitoring changes in land cover and land use.

2.6. Image Classification

In order to examine and assess environmental and socioeconomic applications such as: urban change detection and socioeconomic variables, image classification results with better accuracy are mandatory. Image classification refers to the extraction of differentiated classes or themes, usually land cover and land use categories, from raw remotely sensed digital satellite data (Weng, 2012). Image classification using remote sensing techniques has attracted the attention of research community as the results of classification are the backbone of environmental, social and economic applications (Lu and Weng, 2007). Because image classification is generated using a remotely sensed data, there are many factors that cause difficulty to achieve a more accurate result. Some of the factors are:

- The characteristics of a study area,
- Availability of high resolution remotely sensed data,
- Ancillary and ground reference data,
- Suitable classification algorithms and the analyst's experience, and
- Time constraint.

These factors highly determine the type of classification algorithm to be used for image classification.

There are various image classification methods that can be applied to extract land cover information from remotely sensed images (Lu and Weng, 2007). However, their application depends on the methodology and type of data to be used. Some of these methods are: artificial neural networks, fuzzy-sets and expert systems. In a more specified way, image classification approaches can be categorized as supervised and unsupervised, or parametric and nonparametric, or hard and soft (fuzzy) classification, or per-pixel, sub-pixel and per-field. Some of the most commonly used image classification methods are discussed below.

2.6.1. Object-Oriented Image Classification Methods

This method of image classification is based on identifying image objects, or segments with similar texture, color and tone of spatially contiguous pixels (Gao and Mas, 2008; Weng, 2012). This approach allows for consideration of shape, size, and context as well as spectral content (MacLean and Congalton, 2012). The classification stage starts by grouping the neighboring pixels into meaningful areas. Qian et al (2007) noted that in object oriented classification approach, single pixels cannot be classified rather homogenous image objects are extracted during segmentation step. Image analysis in object-oriented is based on contiguous, homogeneous image regions that are generated by initial image segmentation.

2.6.2. Pixel-Based Image Classification Methods

Pixel-based classification methods automatically categorizes all pixels in an image into land cover classes fundamentally based on spectral similarities (Qian et al, 2007; Weng, 2012). These types of classifiers develop a signature by summing up all pixels. Thus, the developed signature contains the necessary things found in the training pixels but does not contain the influence of mixed pixels (Weng, 2012). According to Tadesse et al (2003), there are two primary types of pixel-based classification algorithms applied to remotely sensed data: unsupervised and supervised.

Unsupervised image classification algorithms are based on categorizing each pixel to unknown cluster centers and then moving from one cluster center to another in a way that the Supervised Spatial Encoder (SSE) measure of the preceding section is reduced data. Whereas in the case of supervised image classification the analyst has previous knowledge about pixels to generate representative parameters for each land cover class of interest. The Maximum Likelihood classification, under the category of supervised classification, which is the most widely used per-pixel method by taking in to account spectral information of land cover classes (Qian et al, 2007).

Although pixel based classification methods have been widely accepted and applicable, however, there are limitations in including spatial pattern during classification. This happened especially in Maximum Likelihood classification methods where they consider only spectral information by neglecting contextual and texture information (Zhou and Robson, 2001; Dean and Smith, 2003).

2.6.3. Contextual Image Classification Approaches

In the case of maximum likelihood classification technique the pixels are assigned to represent classes taken in to consideration and this is done through observing of each pixel. However, there could be misclassification errors especially during the presence of random noise which causes different classes to be appeared similar (Sharma and Sarkar, 1998). To avoid such problems, contextual classification techniques have been chosen which exploits spatial information among neighboring pixels. These techniques are based on the assumption that the response and class of two spatially neighboring pixels are highly related. The advantage of using contextual techniques will improve image classification results by reducing error rates related to spectral properties (Weng, 2012).

2.7. Land use Change Detection Analysis

Change detection can be defined as the process of identifying differences in the state of object or phenomena by observing them at different times by using remote sensing techniques (Singh, 1989). Essentially, it also involves the ability to quantify temporal

effects using multi-temporal data sets. Because of repetitive spatial coverage at short time intervals and consistent image quality, change detection is considered as one of the major applications of remotely-sensed data obtained from Earth-orbiting satellites (Singh, 1989).

Change detection has a wide range of applications in different disciplines such as land use change analysis, forest management, vegetation phenology, seasonal changes in pasture production, risk assessment and other environmental changes (Singh, 1989). The main objective of change detection is to compare spatial representation of two points in time frame by controlling all the variances due to differences in non target variables and to quantify the changes due to differences in the variables of interest (Lu et al, 2004). A change detection research to be good, it should provide the following vital information: area change and rate of changes, spatial distribution of changed types, change trajectories of land-cover types and accuracy assessment of change detection results.

Quantifying land use and land cover changes and applying suitable change detection methods highly depend on the type of changes that happened in landscapes and how those changes are noticeable in images. The changes could be continuous or categorical. According to Abuelgasim et al (1999), change detection in continuous land cover changes focuses on measuring the degree of changes in amount or concentration through time. However, in the case of categorical land cover changes, the goal of change detection is to identify new land cover classes and changes between classes through time.

2.8. Change Detection Techniques using a Remotely Sensed Data

The selection of suitable method or algorithm for change detection is important in producing a more accurate change detection result since constraints such as spatial, spectral, thematic and temporal properties affect digital change detection. Some techniques such as image differencing can only provide change or non-change information, while some techniques such as post classification comparison can provide a complete matrix of change directions. According to Bekalo (2009), different change detection methods could produce different changes of maps depending on the algorithm they followed.

Although there are many change detection methods in remote sensing of image classification, recently researchers divided in to image ratio, image regression, image differencing and the method of change detection after classification (post classification method) (Xu et al, 2009; Bekalo, 2009). The classification of methods mainly depend on data transformation procedures if exists and analysis techniques applied. So, based on these conditions the current common methods of change detection are discussed below:

2.8.1. Image Regression Method

In image regression method of change detection, pixels from time t_1 are assumed to be a linear function of the time t_2 pixels (Singh, 1989). Under this assumption, it is possible to find an estimate of image obtained from t_2 by using least-squares regression. According to Abuelgasim et al (1999), image regression technique takes in to account differences in the mean and variance between pixel values for different dates. This consideration minimizes the influence of differences in atmospheric conditions. In detecting changes of urban areas the regression procedure has more advantage than image differencing technique.

2.8.2. Image Ratio Method

In image ratio method, images must be registered beforehand and rationed band by band. The results of image ratio are interpreted with a threshold of values. If the ratio of the two images is 1, it means that there is no change in the land cover classes where as a ratio value of greater or less than 1 indicates a change in land cover classes (Singh, 1989; Bekalo, 2009). This method rapidly identifies areas of changes in relative terms.

2.8.3. Image Differencing Method

Image differencing is one of the most extensively applied change detection method. It can be applied to a wide variety of images and geographical environment. In this technique, images of the same area, obtained from times t_1 and t_2 , are subtracted pixel wise. It is generally conducted on the basis of gray scale which used to show the spatial extent of

changes in the two images. A threshold value is required for the gray of difference image in order to examine the changed and unchanged regions (Xu et al, 2009).

2.8.4. Post Classification Method

This method is the most simple and obvious change detection based on the comparison of independently classified images (Singh, 1989). Maps of changes can be produced by the researcher which shows a complete matrix of changes from times t1 to time t2. Based on this matrix, if the corresponding pixels have the same category label, the pixel has not been changed, or else the pixel has been changed (Xu et al, 2009).

2.9. Introduction to Land use Change Modeling

Land is utilized for multiple purposes and it is critical that land cover change be monitored and evaluated for both its negative and positive consequences. Dynamic urban land use and land cover change processes caused due to human activities have a wide range of effects on the global climate change either directly or indirectly (Herold et al, 2001; Lambin et al, 2001). It also affect human and natural systems and contribute to changes in carbon exchange and climate through a range of feedbacks. Its future changes are also a function of numerous driving variables (Lambin et al, 2003; Veldkamp and Lambin, 2001). Some of these drivers are population change, economic activity and growth as well as biophysical conditions and are most important at a range of geographic scales.

Bhatta (2010) noted that, the first and foremost reason for urban growth is an increase of urban population. Urban areas attained rapid growth as a result of natural increase in population. This is due to uncontrolled family planning where birth rate is greater than death rate. The second one is migration to urban areas. Where migration is defined as the movement of people from rural to urban areas within the country.

Therefore, modeling of urban growth is a very essential step for further improvement of urban planning and land use management. The rising awareness and importance of land-

use models in the land use and land cover research community has led to the development of a wide range of land-use change models (Verburg et al, 2002).

2.10. Land use Change Models

Because of the significance impacts of land use and land cover changes, the use of land use change models become important to understand these changes and driving factors (Verburg et al, 2004). Models are representations of the real world, based on theoretical assumptions that represent systems (Verburg et al, 2002). Over the past decades, a range of land use change models have been invented by the land use modeling community for the land management needs as well as to analyze and project impacts for the future. Lambin et al (2001) described integrated modeling in a wider scale is an important technique in order to predict future scenarios.

Land use change models are tools which support the analysis of the causes and consequences of land use changes. They provide better understanding of the dynamics of systems to develop hypotheses that can be tested empirically. Verburg et al (2004) reported that they are useful for extracting complex driving forces that affect the spatio-temporal pattern of land use changes and impacts.

Literature has described a number of models depending on different disciplines such as on: landscape ecology, urban planning, statistics and geographic information science (Veldkamp and Lambin, 2001; Verburg et al, 2004). Comparing the performance of models is a complex issue because of its high dependency on disciplinary perspectives, applied methods, data types used and modeling goals. For example: the GEOMOD model simulates change between two land categories where as Markov chain and the cellular automata Markov model simulate change among several categories (Brown et al, 2004).

According to Wainger et al (2007), for different applications of land use change modeling, models were categorized in to three major types as: spatially explicit econometric models, spatial allocation (GIS neighborhood rules) and agent-based models as shown in figure 2.2 below. The criteria to group these models is based on structure and methodologies.

Structure in this case refers to the spatial relationships between the components of a landscape.

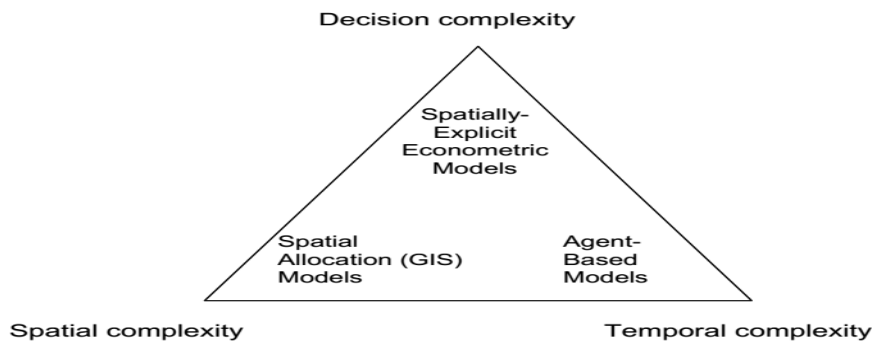


Figure 2.2: Classification of Models based on structure.(Source: Wainger et al, 2007)

2.10.1. Spatially-Explicit Econometric Models

Spatially-explicit econometric models were developed by economists for the purpose of characterizing decisions of agents converting land between uses. The spatially explicit economic models are known by conceptualization of the conversion decision as an economic transaction where expected payoff must exceed costs. The advantage of these types of models is that its ability to share explanatory variables with other types of models developed by other disciplines (Irwin and Geoghegan, 2001). However, these models have limitations of detailed data of regionally consistent formats and also unable to model conditions that deviate from historic norms.

Suarez-Rubio et al (2012) reported that such models provide information by projecting spatial distribution of land use conversion by using transaction data. This enables to determine the maximum profits by considering factors that affect the expected result. Understanding how likely land development is changing with different policy scenarios is one of the expected importance of spatially-explicit econometric models.

As mentioned in previous topics, the availability of infrastructure and better developments as well as recreational areas allowed urban growth is towards to urban-rural fringe driven by increase of population. Suarez-Rubio et al (2012) showed that urban-rural fringe

development in metropolitan areas has showed a growth of more than twice as fast as development in metropolitan urban areas. Their study also emphasized that urban-rural fringe development by the year 2000 covered about 25% of the contiguous United States. Modeling the trend of urban-rural fringe areas therefore important for better management and mitigate the consequences. Thus, spatially explicit models become a good choice to predict land use changes since they consider social and environmental causes and consequences (Cabral and Zamyatin, 2009).

2.10.2. Spatial Allocation Models

Spatial allocation models have been developed for the purpose of identifying neighborhood conditions that have connections with land conversion specifically for residential and commercial development. They can also be used for generating future land use changes. A transition rule is required for modeling the drivers of changes of new land use. Verburg et al (1999) also noted that the spatial pattern of land use through time can be determined by the components of landscape such as: human factors (population, technology and economic conditions) and biophysical constraints (soil, climate and topography). In order to describe the relationships between these factors, a decision rule is used. These models have the capability of generating a diffusion of growth near the areas of existing urban centers. Thus, there should be sufficient growth rules which help to generate new urban centers by limiting the diffusion otherwise variables that recognize patterns of land use must be considered (Wainger et al, 2007).

2.10.3. Agent-Based Models

Agent-based models comprises of simulation models where much attention has been given by the land use research community. They characterize systems in terms of independent but interconnected “agents” that have the ability to make “decisions” based on changing conditions. For most of the agent based models which used for land use modeling, higher temporal complexity could be taken as an accurate criteria to be chosen (Parker et al, 2002). The majority of these models are referred to as cellular models which includes

spatial modeling techniques such as cellular automata and Markov models. However, Parker et al (2003) showed they have different applications as cellular models focused on landscapes and transitions, where as agent-based models focused on human actions.

Agent based models have a wide range of applications such as archaeological reconstruction of ancient civilizations, modeling of infectious diseases as well as modeling of economic processes. Matthews et al (2007) have identified the five purposes of agent based models in the land use modeling community. These are policy analysis and planning, participatory modeling, explaining spatial patterns of land use, examining social science concepts and demonstrating land use functions.

Cellular Automata (CA) is a discrete dynamic system in which space is divided into regular spatial cells and time progresses in discrete steps. CA models can generate complex global patterns based on transition rules for simulation processes. The transition rules determine how a cell will evolve under certain conditions. These models have been widely used for simulating urban sprawl and land use dynamics (Cao et al, 2013). This study has integrated Markov chain model and Land Change Modeler. The descriptions and approaches of these models are discussed below.

2.11. Markov Chain Models

Markov chain models are relatively simple and more powerful to model complex processes and changes in land use for planning purposes. They provide better information for analyzing time series of system evolution (Levinson and Chen, 2005). A Markovian process is one in which the state of a system at time t_2 can be predicted by the state of the system at time t_1 given a matrix of transition probabilities from each cover class to every other cover class.

A stationary property is one of the importance of these models since it integrates a transition probability matrix. This property is critical to Markov chain model especially for future predictions of land use. The stationarity of the transition matrix in turn helps to

inspect the validity of the model (Iacono et al, 2012). The MARKOV module in IDRISI can be used to create such a transition probability matrix (Eastman, 2012).

Markov Chain model to be considered as a system, it has to satisfy the following properties:

- The sum of the rows of the probability matrix must be one
- The probabilities of the transition matrix must be the same for any two periods
- Probabilities have no memory, that is, the state tomorrow depends only on the state today (the Markov condition)
- Time periods must be uniform in length or duration.

Markov chain model has a good quality of simplicity. It can also describe complex and long-term process of land use conversion in terms of simple transition probabilities.

2.12. Land Change Modeler

Land Change Modeler (LCM) for Ecological Sustainability is an integrated software environment within IDRISI oriented to the pressing problem of accelerated land conversion and the very specific analytical needs of biodiversity conservation. It was developed by Clark Labs for the purpose of assessing a variety of land change scenarios and contexts. This model adopts the Markov Chains analysis for time prediction, but with an automatic Multi-Layer Perceptron for a spatial allocation of simulated land cover scores (Eastman, 2012).

In LCM, according to Eastman (2012), tools for the assessment and prediction of land cover change and its implications are organized around major task areas: change analysis, change prediction, habitat and biodiversity impact assessment and planning interventions. Also, there is a facility in LCM to support projects aimed at Reducing Emissions from Deforestation and Forest Degradation (REDD). The REDD facility uses the land change scenarios produced by LCM to evaluate future emissions scenarios. Because of its ability

to integrate various transitions involving same explanatory variables in to a single sub model, LCM is applied in this study.

From the reviewed literatures, Haregeweyn et al (2012) have investigated urban expansion in the urban fringe of Bahir Dar area, Ethiopia. Zeleke and Hurni (2001) also found a significant impacts of dynamic land use and land cover changes in the northwestern Ethiopian Highlands. Both studies applied remote sensing and GIS techniques to quantify land use and land cover changes. Moreover, Haregeweyn et al (2012) have tried to project urban expansion by applying a relationship between total population and urban area with time. However, none of these studies did apply any land use change model to integrate factors that influence (explain) urban expansion other than population. Thus, this study has a great contribution in applying LCM for simulating as well as projecting changes in land use and land cover in Bahir Dar area, Ethiopia as a result of driving variables. It also considered some factors that are assumed to explain changes in the growth of urban areas.

CHAPTER THREE

3. DATA AND METHODOLOGY

3.1. Description of the Study Area

Bahir Dar is located in the north western part of Ethiopia with a total area of about 625 km². Geographically it is located at 11° 36' N and 37° 23' E. It incorporates the core city of Bahir Dar with three small urban centers as (satellite towns); namely Zegie, Tis Abay and meshenti with their rural vicinities as the council of Amhara National Regional State (ANRS) has named under the revised proclamation No. 91/2003. In relative terms, Bahir Dar is found at a distance of 567 km from the capital city of Ethiopia, Addis Ababa along the road Addis Ababa - Debre Markos. It is one of the leading tourist destinations in Ethiopia, with a variety of attractions in the nearby Lake Tana and Blue Nile river (Haimanot, 2009).

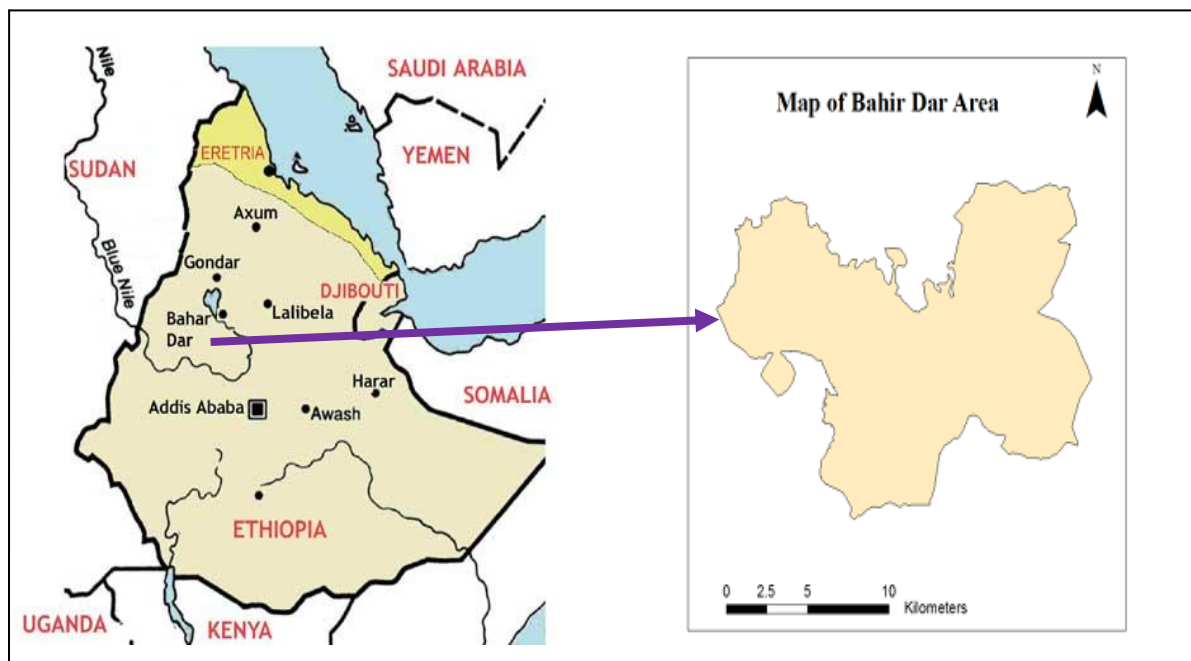


Figure 3.1: Map of the study area

3.1.1. Population

The first national population and housing census was conducted in 1984 and the population of Bahir Dar was 54,800. After 10 years in 1994, the second census has also been conducted and the total population was 96,140 with an increase of about 75% from 1984. In 2007, the total population has become 180,174. The value increased by about 87% of the population of 1994 according to the CSA.

Year	Total Population
1984	54,800
1994	96,140
2007	180, 174

Table 3.1: Total Population of Bahir Dar 1984-2007 (Source: CSA, 2008).

3.1.2. Physiographic Nature of the Study Area

The city stretches over a predominantly flat land with hardly noticeable slope change. The elevation variation in the area ranges from 1,786 m.a.s.l near the lakeshore to 1,886 m.a.s.l at Bezawit. The general slope orientation of the town is slightly towards Abay River, which crosses the city proper from north west to south east and serves as the only out let for surface water runoff from the town. Although there is no well- defined course of surface water, the direction of drainage is dominantly towards Abay river except for some areas, which drain in to Lake Tana. Because of its extreme flatness, the town has been affected by flood problem (Haimanot, 2009).

3.1.2.1. Topography

Bahir Dar metropolitan area is mostly characterized by flat plain topographic landscape although there have been some pockets of land with hills, rugged and undulating features. The elevation of the metropolitan area falls in between the range of 1650 m.a.s.l (around Tis Abay Fall) and 2100 m.a.s.l (around Meshenti). When it is viewed specifically, the

average elevation of Bahir Dar is estimated in between as low as 1786 m.a.s.l (near the lake shore) and as high as 1886 m.a.s.l (near Bezawit hill).

In general, the predominance of flat landscape and plain topography in this area has a promising opportunity to undertake various urban development activities in the centers and their vicinities in particular and in the whole metropolitan area in general notwithstanding the adverse flooding and water pounding problems. On the other hand, the hilly and rugged (undulated) land features in and around these urban centers are identified as one of the major problem areas for any development activities calling for metropolitan intervention (Bahir Dar City Administration, 2013).

3.1.2.2. Geology

The rocks exposed in Bahir Dar area mainly include basaltic lava flows (lava outpourings and dames) and related spatter cones. The basaltic lava flows basically comprise periphrastic and aphanites basalts. And the overall exposed thicknesses of the flows vary from few meters to more than 100 meters at Bezawit. They seem to occur as alternate flow layers in some places and are often highly weathered and fractured particularly at depth, as bore hole log data reveals (Bahir Dar City Administration, 2013). Generally, the rocks out cropping in Bahir Dar regional administration can be categorized based on lithology variation as Aphyritic Basalt, Vesicular Basalt and Scoria cereous Basalts.

3.1.2.3. Climate

Because of the complexity of climate in the region, several classification systems have been applied to the Ethiopian situation. Some of these are: Traditional, Koppen's, Throthwaite's, Rainfall regimes and Agro-climatic zone classification systems. Among these classification systems, the traditional system is most commonly used, based on altitude and temperature. Thus, the country is divided into five climate zones such as: Bereha (dry hot climate with < 500m altitude), kola (hot and arid type with an altitude of 500 -1500m), weina dega (dry warm climate having 1500 - 2500m altitude), dega (cold

with 2500 - 3500m altitude) and wurch (very cold or alpine with altitude > 3500m) (Walker et al, 2003).

The mean annual precipitation depth recorded at Bahir Dar Station in 37 years period from 1962 to 1999 is about 1437mm. There is a significant seasonal variation in the amount of rainfall. Almost 60.3% of the mean annual rainfall occurs in two raining months of July and August with maximum mean value of more than 432mm (Haimanot, 2009).

The monthly mean maximum and minimum temperature records of Bahir Dar in the year between 1961 and 2000 showed that the highest mean monthly maximum temperature occurs in April (29.7⁰c) and lowest in July and August (23.3 ⁰c). While the mean monthly minimum temperature ranges for the lowest from 7.1⁰c in January to the highest 14.2⁰c in the months of May (Haimanot, 2009).

3.1.2.4. Hydrology

In the study area there is one major international river called "Abay" which is originating at Lake Tana in Ethiopia and crosses Sudan and Egypt. It has a total length of 1,450 kilometers of which 800 km are inside Ethiopia. The discharge data from 1960 to 2001 at Bahir Dar gauging station indicates the mean annual flow of the river Abay is about 123.07m³/s (Bahir Dar City Administration, 2013).

Lake Tana is the source of Blue Nile covering an area of more than 3000 km². Thus, Lake Tana and river Abay made Bahir Dar as one of the leading tourist destinations in Ethiopia, by having a variety of attractions (Bahir Dar City Administration, 2013).

3.2. Methodology

In this section the general methods implemented, applied techniques and the data inputs used throughout this study were explained briefly in the designed flow figure 3.2 below.

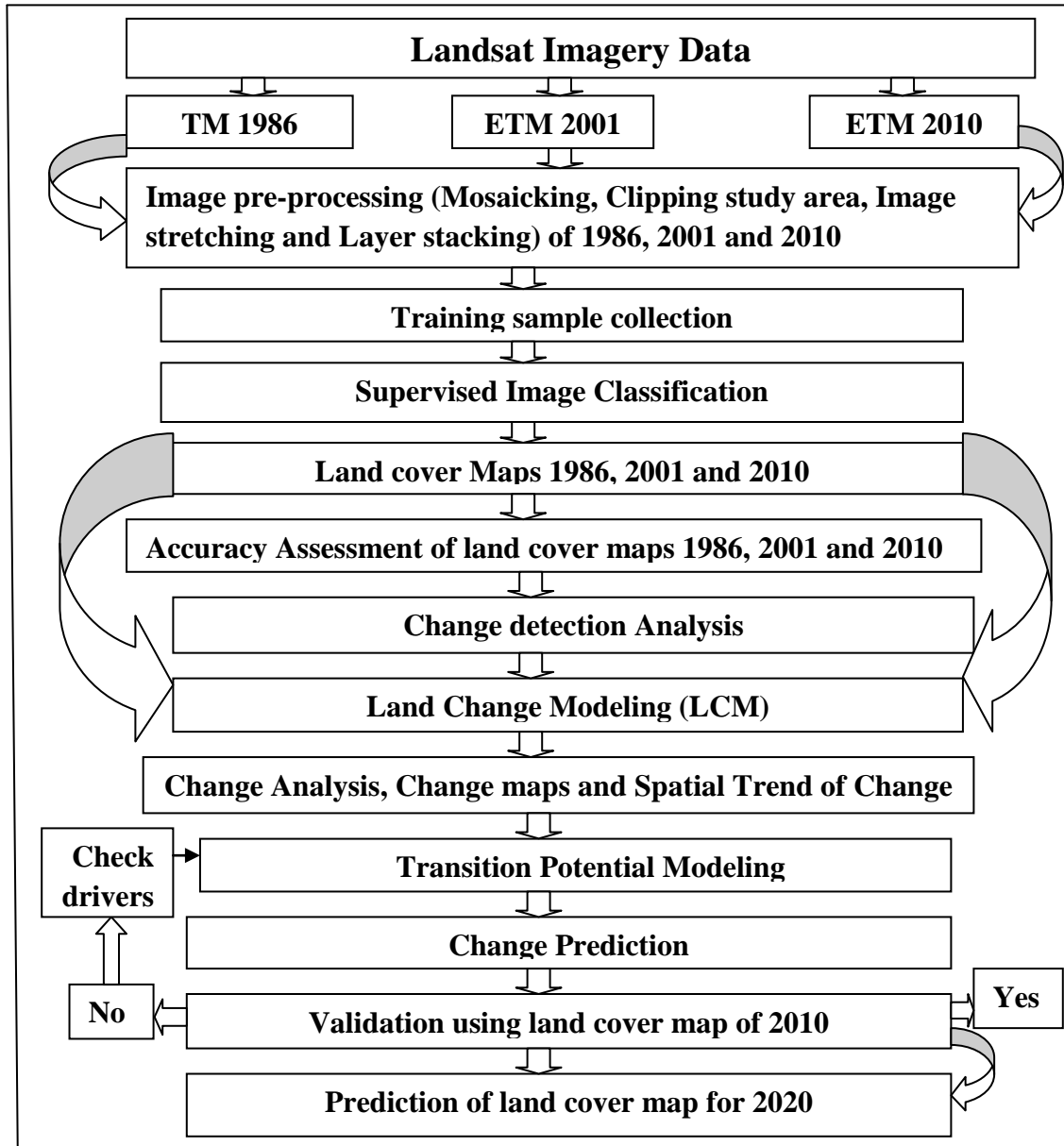


Figure 3.2: Flow chart of the methodology.

As shown in the above figure, the first section of the methodology involved on preprocessing of data, remote sensing image classification and change detection analysis.

After having classified land cover images, the next step was applying land use modeling through LCM by incorporating explanatory variables to model transitions of land cover changes between 1986 and 2001 for further prediction to 2010. Finally, validation of model results has been implemented and assessed. Depending on the validation results and model accuracy, future prediction of changes for 2020 would be done. The details of the selected flow chart methodology of this study were explained in the following subsections:

3.2.1. Data and Processing

There are different methods and techniques in order to use an input data to reach in success of a desired goal. However, it highly depend on the availability of input data and quality of information. The data sets used in this study were Digital Elevation Model (DEM), land use and land cover data, river and road data. A 30 m by 30 m resolution ASTER DEM of the study area was obtained from NASA website with the same projection as the images and indicated in appendix A (figure A.5). The shape files of study area, river and roads were collected from the Ethiopian Mapping Agency and Geofabrik website respectively.

In this study Landsat imageries of TM and ETM+ were employed and acquired in the same season and the same level of resolution for the periods 1986, 2001 and 2010. Thus, it was conducive for comparison of changes and patterns occurred in the time under discussion. The images were downloaded from the Global Land Cover Facility of the University of Maryland (GLCF, 2013) and the United States Geological Survey (USGS) and spatially referenced in the Universal Transverse Mercator (UTM) projection with datum World Geodetic System (WGS) 1984 UTM zone 37N. The images were extracted to Tiff formats for processing and the detail of image properties are summarized in table 3.2 below

Sensor	Acquisition time	Spatial resolution	Path/Row	Producer
Landsat TM	03/01/1986	30 m	170/052	GLCF
Landsat ETM+	05/02/2001	30 m	170/052	GLCF
Landsat ETM+	23/12/2010	30m	170/052	USGS

Table 3.2: The characteristics of landsat satellite data used in this study

Satellite bands were composed in different ways in order to identify surface features in the study area. True color composite usually known by RGB 321 combination where band 3 reflects red color, band 2 reflects green and band 1 reflects blue color. Another composite called "false color composite" which uses an RGB combination of 432. In this band combination band 4 represents the NIR infrared, band 3 belongs to red and band 2 to green. This combination gives better visualization in identifying vegetation which looks red in 432 combination. Figure 3.3 below illustrated maps of the study area generated using the false color (432) combination and vegetation is seen as red and dark red, water is blue and shades of blue.

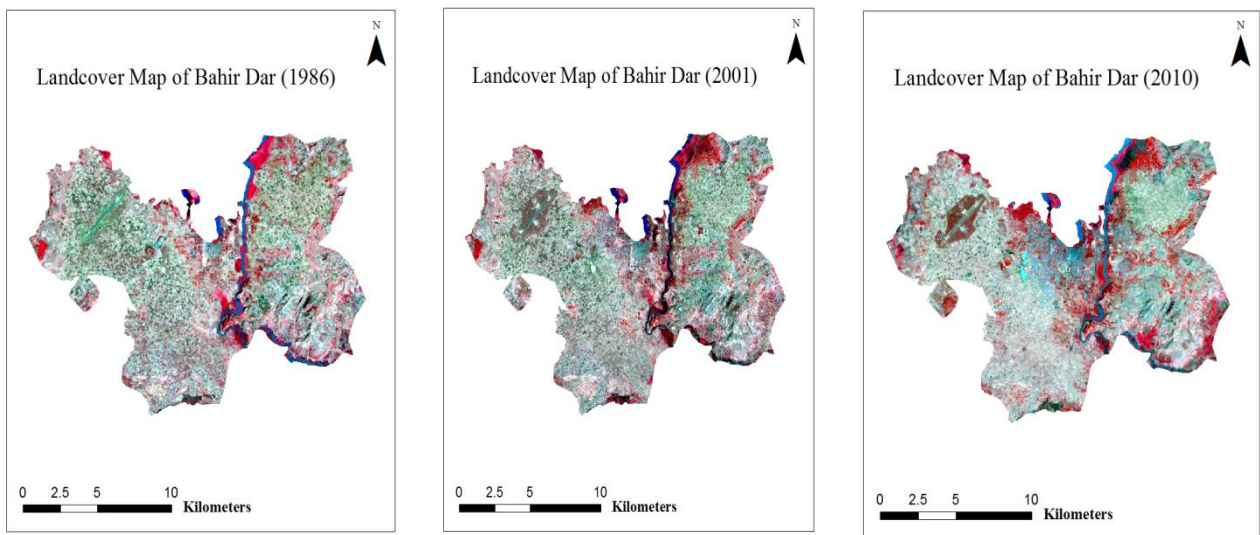


Figure 3.3: False color composite of 1986 (left), 2001 (middle) and 2010 (right).

3.2.2. Nomenclatures of Land cover Classes

In almost any classification process, it is rare to find clearly defined classes that one would like. Before collecting training samples, the land cover classes should be known so as to make the classification easier (Bekalo, 2009).

CORINE land cover is a map of the European environmental landscape based on interpretation of satellite images. It provides comparable digital maps of land cover for each country for much of Europe. This is useful for environmental analysis and for policy makers to design suitable methods. CORINE stands for *Coordination of Information on the Environment*. The European Union established CORINE in 1985 to create pan-European databases on land cover, biotopes (habitats), soil maps and acid rain. It gives useful geo-referenced information for disaggregation (Kleeschulte and Büttner, 2006). This geographic database provides information that is spatially more detailed than the commune limits.

Land cover classes	Description
Artificial (Built-up) surfaces	Consists of Urban fabric, Industrial, commercial and transport units, Mine, dump and construction sites, and artificial non-agricultural vegetated areas
Agricultural areas	Arable land, Permanent crops, Pastures and Heterogeneous agricultural areas
Forests and semi-natural areas	Forests, Shrub and/or herbaceous vegetation association
Open/barren areas	Open spaces with little or no vegetation, beaches, dunes sands, bare rocks, sparsely vegetated areas
Wetlands	Inland wetlands and Coastal wetlands
Water bodies	Water courses, water bodies, sea and ocean areas, coastal lagoons

Table 3.3: Land cover classes nomenclature (Source: CORINE land cover project European Environment Agency (EEA)).

3.2.3. Image Classification

Image classification refers to the task of extracting information of classes from a multiband raster image. The resulting raster from image classification can be used to create thematic maps. Classification schemes may be comprised of hard, discrete categories; in other words, each pixel is assigned to one, and only one, class. Fuzzy classification schemes allow a proportional assignment of multiple classes to pixels. The entire image scene may be processed pixel-by-pixel, or the image may be decomposed into homogeneous image

patches for object-oriented classification. As stated by Jensen (2005), “no pattern classification method is inherently superior to any other”. It is the responsibility of the researcher, using his or her knowledge of the problem set, the study area, the data sources, and the intended use of the results, to determine the most appropriate, efficient, time and cost-effective approach (Jensen, 2009).

For this study, land cover maps were generated based on the pixel based supervised classification through a number of processes. The first step was collection of training samples for each land cover classes which typically representative for land cover classes. These samples were collected based on the researcher's personal experience and physiographical knowledge of the study area. Moreover, image enhancement and composition were applied for better determination of land cover classes. Using these approaches more than 350 training samples were collected for each Landsat imagery. The next step was performing the image classification using the Maximum Likelihood Classifier through ArcGIS. In this stage a number of both classification and reclassification procedures were used in order to improve the classification and neglect misclassified cells.

Finally, the accuracy assessment of the classified images were assessed by using the original mosaic and the Google Earth images. For performing this analysis a randomly selected points have been taken as references for the land cover maps of 1986, 2001 and 2010.

3.2.4. Accuracy Assessment

Accuracy assessment is a general term for comparing a classification to geographical data that are assumed to be true, in order to determine the accuracy of the classification process. It is performed by comparing a map created by using remote sensing analysis to a reference map based on different information sources such as Google earth and original mosaic images for those time periods where Google earth is not available. An interpretation is then made of how close the newly produced map from the remotely-sensed data matches the reference (source) map. Although the basic approaches to

accuracy assessment seems relatively direct and easy, a variety of errors encountered when evaluating an image classification and capturing remotely sensed data. Evaluation of the accuracy of a classified image can be done using an error matrix sometimes called confusion matrix (Senseman et al, 1995; Foody, 2002).

Error Matrix is a square array of numbers laid out in rows and columns that expresses the number of sample units assigned to a particular category relative to the actual category as verified in the field. The columns normally represent the reference data, while the rows indicate the classification generated from classified image. It also provides an excellent summary of the two types of thematic error that can occur, namely, omission and commission. Error of omission refers to pixels in the reference map that were identified as something other than their "accepted" value. Whereas error of commission, on the other hand, refers to pixels that were incorrectly classified as a class in a row (Senseman et al, 1995; Maingi et al, 2002).

Most of the classification accuracy measurements are derived from an error matrix. However, the most popular one is the correctly allocated cases in a percentage. Based on this, user 's accuracy refers to the probability that a given pixel can be found in the ground as it is in the classified image, whereas producer's accuracy refers to the percentage of a given class that is correctly identified on the map (Yesserie, 2009).

In this study, a total test samples of 226 for image 1986, 104 for image 2001 and 242 for image 2010 were randomly selected respectively from the original mosaic image of 1986 and Google earth for the images 2001 and 2010. The researcher has examined the test sample plots and assigned a class value to each. The accuracy assessment was conducted for each classification result. Thus, agreement and disagreement of the analysis is evaluated by using an error matrix and simple descriptive statistics.

3.3. Application of LCM for Land use Modeling

LCM is applied in this study to analyze land cover changes, evaluate transitions from one land cover state to another, simulate future land change scenarios and model species

impacts. It is an innovative land planning and decision support software tool used for conservation prioritization and planning efforts. The software is included in IDRISI Selva GIS and Image Processing software and is available as an extension for use with ESRI's ArcGIS product (Land Change Modeling in IDRISI, 2014). Thus, to perform LCM in this study, two land cover maps from different dates (1986 and 2001) were required for change analysis and prediction in the future. The analysis performed in this particular study followed three stages in LCM modeling of land use changes:

3.3.1. Change Analysis with LCM

The change analysis panel provides a rapid quantitative assessment of changes, allowing the researcher to generate evaluations of gains and losses, net change, persistence and specific transitions both in map and graphical form. It also provide a means of generalizing the pattern of trend between two land cover map transitions (Eastman, 2006).

In this study, land use and land cover maps of the study area obtained from image classification for the periods of 1986 and 2001 were used for the analysis. Based on the principle of land change analysis, maps of gains and losses, contributions to net change, transitions of land cover classes between different categories and spatial trend analysis were examined both in map and graphical form.

3.3.2. Transition Potential Modeling with LCM

This tab is designed to create transition potential maps of acceptable accuracy in order to run the actual modeling. It provides group transitions in to a set of sub models and to explore the potential power of explanatory variables. Variables can be added to the model either as static or dynamic components based on their effect to urban expansion (Eastman, 2012). Static variables express aspects of basic suitability for the transition under consideration, and are not changing over time. Whereas dynamic variables are time-dependent drivers such as proximity to existing development or infrastructure and are recalculated over time during the course of a prediction.

3.3.2.1. Transition Sub-Models Status

This panel lists all transitions that exist between the two land cover maps of time 1 and time 2. The researcher should specify which transitions to be considered for producing the transition potentials (Eastman, 2012). In the case of this study area, transitions from all land cover classes to built up areas between 1986 and 2001 were considered as the aim of the study focus on built up areas. Moreover, major transitions between other land cover classes have been incorporated since it has a great role in the dynamism of the study area. For better results on the accuracy of Multi-layer Perceptron, major transitions have been included in the transition sub model (Eastman, 2006). Based on this principle, transitions such as; transition from all land cover classes to built-up areas, agriculture to open areas, agriculture to forest and semi-natural areas were considered in this study.

In order to model these selected transitions in LCM, Logistic Regression and Multi-layer perceptron are available. Because it can run multiple transitions, up to 9, per sub-model, the Multi-layer Perceptron neural network has been used in this study area. Thus, the six transitions selected in this study were set in to sub-model status and named as one sub-model name. The next step was to develop variables that explain these six transitions. In this study both static and dynamic variables have been used.

3.3.2.2. Model Variables Development for Bahir Dar Area

After analyzing the land use and land cover changes between 1986 and 2001 in Bahir Dar and identifying the major transitions, modeling of these transitions have been performed with selected variables. In LCM, model running is performed twice: in this study, the first run was to generate a map of transition potential after the selected variables were incorporated. In the second time, the model has been run for generating a prediction map based on the produced maps of transition potential.

Steiner et al (2000) mentioned that for the purpose of modeling the selected transitions, variables or suitability maps should be created for accurate and desirable direction of future development in built up areas. Suitability analysis techniques incorporate three

different factors of an area: location, development activities, and environmental processes and these are important for decision-making (Al-Shalabi et al, 2006). A criterion is some basis for a decision that can be measured and evaluated. It is the evidence upon which an individual can be assigned to a decision set. The suitability range is the decision rule that restricts or allows particular land uses to grow up or transform among each other. Criteria can be of two kinds: factors and constraints (Eastman, 2012).

There are many factors responsible for urban growth such as increasing of population and rapid urbanization. However, there are also inhibiting constraints for urban development growth such as topography, water bodies and already developed areas.

3.3.2.2.1. Constraints

Constraints are variables which restricted or limit the growth of development such as urban land use. They are expressed in the form of a Boolean (logical) map: areas excluded from consideration being assigned a value of 0 (unsuitable) where as those considered ones with a value of being 1 (suitable) (Eastman, 2012). The constraints considered in this study were major roads, existing built-up areas derived from image classification of land cover map 1986 and major rivers as shown in figure 3.4 below.

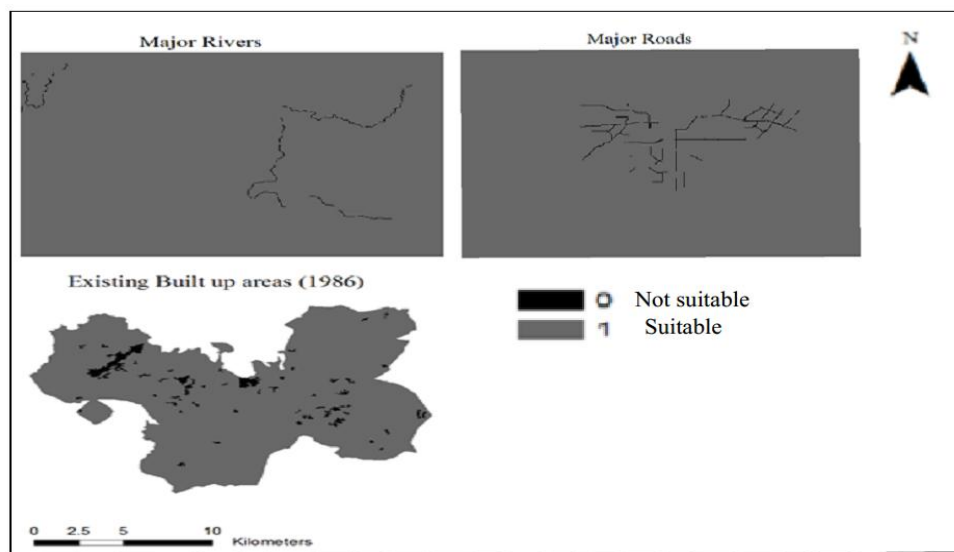


Figure 3.4: Constraints

The map of existing built up area indicated in figure 3.4 was extracted from the classified land cover map of 1986. The shape file data for major roads and rivers was taken from Geofabrik website for the study area which is freely available (Geofabrik, 2013).

3.3.2.2.2. Factors

Factors are criterion that enhances or detracts from the suitability of a specific alternative for the activity under consideration. They are not reduced to simple Boolean constraints. It is therefore most commonly measured on a continuous scale (Eastman, 2012). Because of the different scales upon which criteria are measured, it is important to standardize the factors to a continuous scale of suitability. In IDRISI, the FUZZY module is provided for the standardization of factors using a whole range of fuzzy set membership functions. Because the Multi Criteria Evaluation (MCE) module has been optimized for speed using a 0-255 byte level of standardization, it is recommended to standardize the factors in this scale (Eastman, 2012). Based on the potential behavior of the local population towards land-use development four factors were selected in this study; distance from major rivers, distance from major roads, distance from existing built up areas and slope and calculated based on the physical distance.

Araya and Cabral (2010) described three fuzzy standardization functions in order to design a criteria for factors to be used in a decision rule. These were sigmoid, J-shaped and linear functions with adjustable settings. Based on this principle, factors in this study were standardized and categorized.

For existing built up areas (map for 1986) a linear monotonically decreasing function has been applied. Since areas close to currently developed land are more suitable than areas farther from developed land which means that suitability decreases with distance. Thus, the control points considered were $c = 0$, $d = 6000\text{m}$ using the fuzzy membership function and indicated in figure 3.5 below.

In the case of roads, a linear symmetric function was considered as the area within 25 m is not suitable for urban growth. However, between 25 m and 9632 m is decreasing with the

highest suitability being near to a 25m. Therefore, $a = 0$, $b = 25\text{m}$, $c = 25\text{m}$ and $d = 9632\text{m}$ values were taken in to account during the fuzzy standardization as shown in figure 3.5.

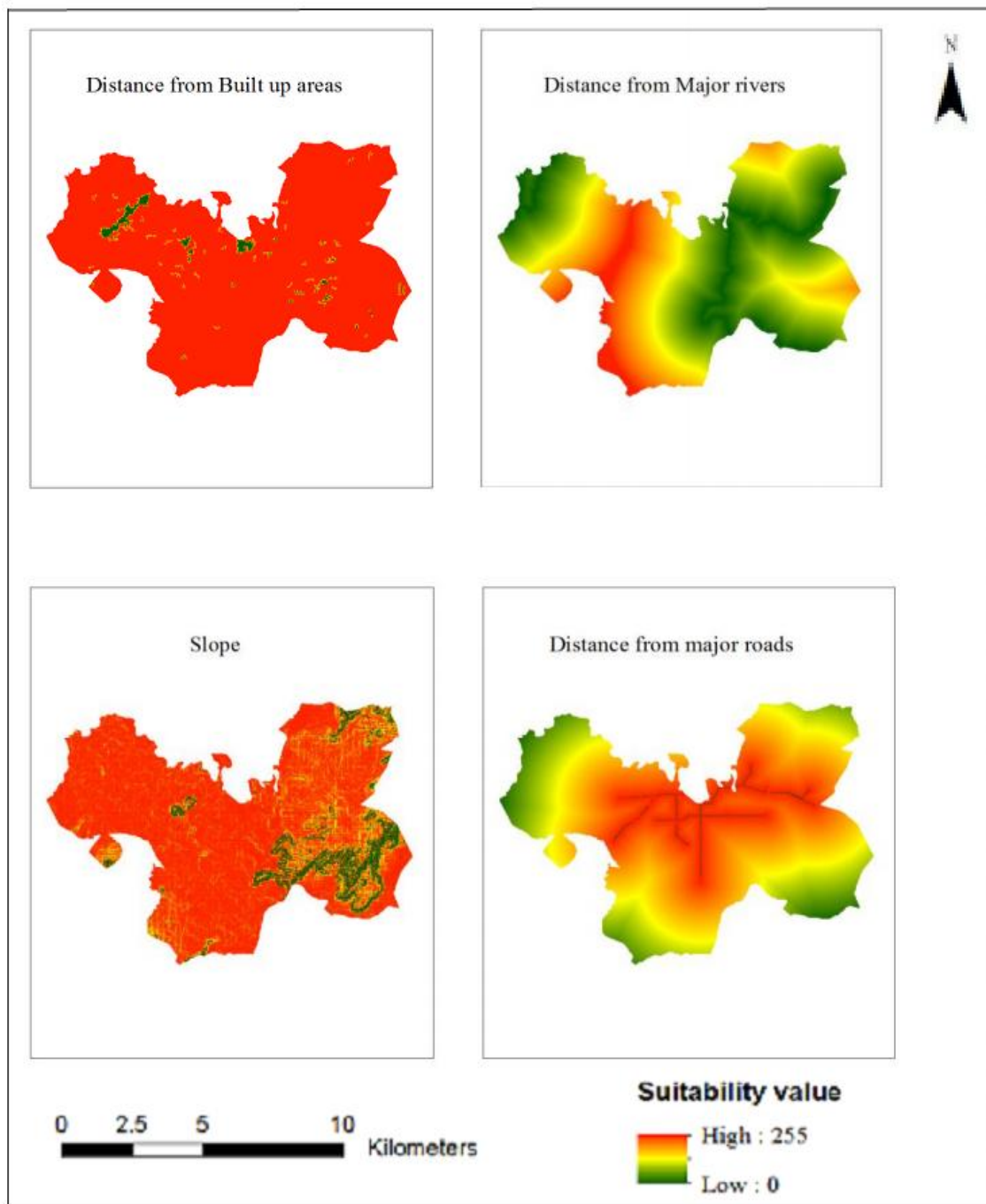


Figure 3.5: Maps of standardized factors.

Rivers were standardized based on their suitability to urban growth so that areas within 30m were restricted as a buffer zone and considered as unsuitable. A linear monotonically increasing function therefore has been applied since suitability increases with distance and $a = 30\text{m}$ and $b = 6000\text{m}$ as seen from figure 3.5 above.

For slope considerations a sigmoidal monotonically decreasing function was applied as regions with slopes $> 15\%$ were considered as unsuitable for urban development. However, regions between 0 and 15% were taken in to consideration of suitable and the control points in this case were $c = 0$ and $d = 15$. Slope has been extracted from DEM of Bahir Dar. Figure 3.5 above presented a suitability map of standardized factors with a common continuous scale of suitability from 0 (least suitable) to 255 (the most suitable). Areas with more red color indicates highest suitability of 255 where as the dark green color represents a lower suitability value of 0.

3.3.2.3. Test and Selection of Site and Driver Variables

In the IDRISI selva edition of LCM after the change analysis tab, the next procedure is to model the transitions. Before doing this, the variables created for the modeling process have been tested using the quick exploratory tool available in the Test and Selection panel. This quick parameter indicates the degree to which the variables are associated with the distribution of land cover categories (Eastman, 2012). The Cramer's V, which measures the association for nominal variables developed with the overall classes, have a range of values from 0 to 1. A high Cramer's V indicates that the potential explanatory value of the variable is good. However, this does not guarantee a strong performance since it cannot account for the mathematical requirements of the modeling approach used and the complexity of the relationship. But, it is a good indication that a variable can be discarded if the Cramer's V is low. A value of 0.15 or higher are considered to be important whereas 0.4 or greater than this being good. The variables or factors tested and used in this study were distance to major roads, distance to existing built-up areas, slope and distance to major rivers and indicated in figure 3.5 above. These variables were tested using this panel to check their performance for explaining urban growth.

3.3.2.4. Transition Sub-Model Structure

In this panel the selected and tested driver variables for a specific sub-model were specified to create transition potential maps for each sub-model in turn. Variables can be added as static and dynamic based on their influence. Dynamic variables are time-dependent drivers such as proximity to existing development or infrastructure and recalculated over time during the course of prediction. Thus, the variables selected in this study as a dynamic state were distance to existing built-up areas and distance to major roads. Whereas static variables express aspects of basic suitability for the transition under consideration, and unchanging over time. Based on this, the variables slope and distance to major rivers were considered as static in this model run. Once model variables have been selected here, the next step was to select Multi Layer Perceptron method for generating transition potential maps (Eastman, 2006).

Multi Layer perceptron (MLP) is a feedforward artificial neural network (ANN) with one or more layers between input and output layers. The term feedforward indicates the flow of data is in one direction from input to output layer (forward). MLPs are widely applicable for classification and prediction of land use changes. It can also solve non linear separable problems (Ahmed and Ahmed, 2012). The main idea of MLP neural network performed in this study was to analyze the changes in built-up areas over the selected years since it can run multiple transitions, up to 9, per sub-model. It was based on the major transitions of land cover classes to built up areas which contributed most. The transitions considered here were: transition from all land cover classes to built up areas, agricultural areas to open areas and agricultural areas to forest and semi-natural areas.

MLP is composed of interconnected neurons or nodes and consists of input, hidden and output layers as indicated in figure 3.6 below. As stated by Gardner and Dorling (1998), the mapping between the input and output vectors become nonlinear which is one of the characteristics of MLP. The nodes are connected by weights. Output signals which are a function of the sum of the inputs to the node modified by a simple nonlinear continuous activation function. The training algorithm determines the individual weights in MLP

using back propagation (BP) algorithm. The training procedure rely on a relatively simple concept such that: if a wrong answer is executed by the network, the weights are modified or corrected so that the error is minimized. Thus, the responses of the network in the future are more likely to be fit or correct.

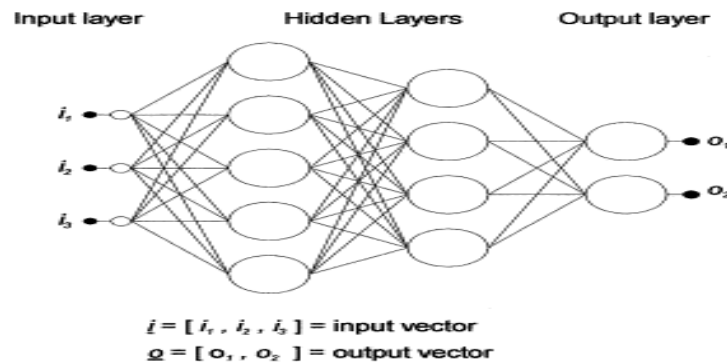


Figure 3.6: Illustration of a three-layered MLP, (Source: Gardner and Dorling (1998)).

In this particular study, samples were extracted from the two land cover maps (1986 and 2001) of areas underwent the transitions being modeled as well as the areas that were eligible to change but didn't. Thus, the minimum cells that transitioned from 1986 to 2001 per class were 1067 for MLP run with 10,000 iterations. The model skill showed that neural network has been fed eight classes with six transition classes where cells have been transitioned and another two persistent cells of classes. The final step of transition potential modeling was running the transition sub model to create the transition potential maps. Thus, the generated potential maps were used to predict land use changes for futures dates.

3.3.3. Change Prediction and Validation

At this last stage, the model is run for change prediction to a specified future date for the allocation of land cover changes (Eastman, 2006). The default procedure, Markov Chain analysis, has been run for this study to determine the amount of change using two land cover maps (1986 and 2001) along with the date specified. The procedure determines exactly how much land would be expected to transition from the later date (2001) to the

prediction date (2010) based on a projection of the transition potentials into the future and creates a transition probabilities file.

In the Change Allocation panel, which used to predict future scenarios, there are two basic models of change are provided. These are a hard prediction model and a soft prediction model. Because the soft prediction yields a map of vulnerability to change for the selected set of transitions, it is preferred to be used in this study. Thus, a map for 2010 of study area has been simulated in order to compare with the ‘actual’ land cover map of 2010.

Finally, the validation panel which allows to determine the quality of the prediction land use map in relation to a map of reality. It has been evaluated by running a 3-way cross tabulation between the later land cover map (a map of 2001), the prediction map (simulated map of 2010), and a map of reality (actual map for 2010). Pinto et al (2009) showed that the overall quality of land cover maps generated from model simulations should be evaluated using kappa statistics parameter.

Modeling of land use and land cover changes for future time is important to know the possible scenarios. In the case of Bahir Dar area, in order to model for future time the following assumptions were set:

1. The modeling process for the year 2020 was depending on the assumption that the nature and developments in Bahir Dar stayed similar to the transitions of land use and land cover changes between 1986 and 2001. This means that the regulations for urban development were kept constant.
2. As designed in section 3.2, flow chart of figure 3.2, a further prediction of land use and land cover change for the year 2020 would be modeled after validation of the model for simulating changes for 2010. If the model would get an acceptable level of accuracy then, prediction for 2020 would be done. However, if the model wouldn't achieved an acceptable accuracy, it is not recommended to perform a future projection.

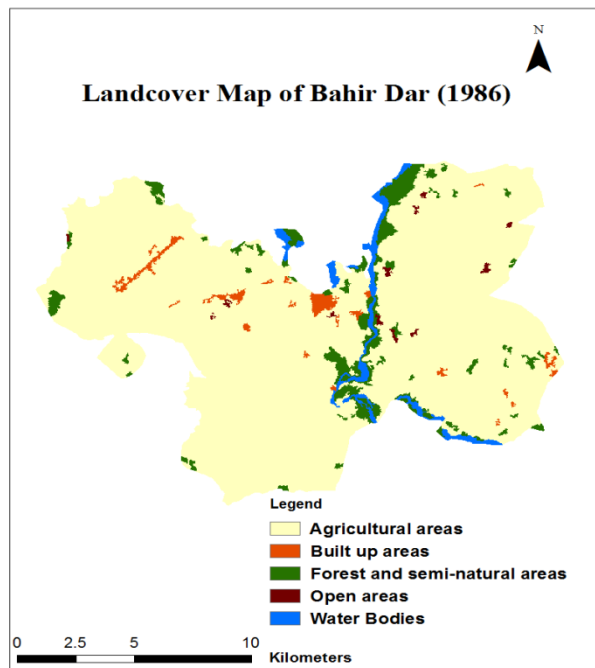
CHAPTER FOUR

4. RESULTS AND DISCUSSIONS

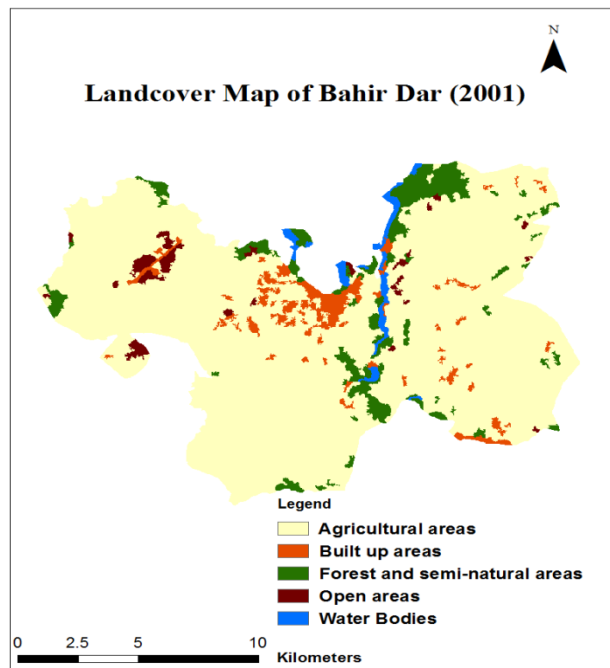
4.1. Classification and Validation results of Land cover Maps

The land cover maps generated after running a maximum likelihood supervised classification as well as a post classification algorithm are presented in figure 4.1 below. As shown from the figures, there has been an increase of built up areas with respective values 1.5% of the study area in 1986 to 4.1% in 2001 and 9.4% in 2010 indicated in table 4.1. Forest and semi-natural areas and open areas have also shown a consistent increase between the study periods with values presented in table 4.1 below. However, there have been a decrease of agricultural areas as clearly shown in figures 4.1a, b and c. In 1986 agricultural areas covered 90.2% of the study area. From figure 4.1 below and table 4.1, agricultural land was the most dominant land cover class in the study area but showed a continuous decrease from 85.8% by 2001 to 74.7% in 2010. Because of the successive decrease of agricultural areas, built up areas have dynamically increased in the study periods. This could be due to an increase of population growth associated with high demand for land and urban supplies.

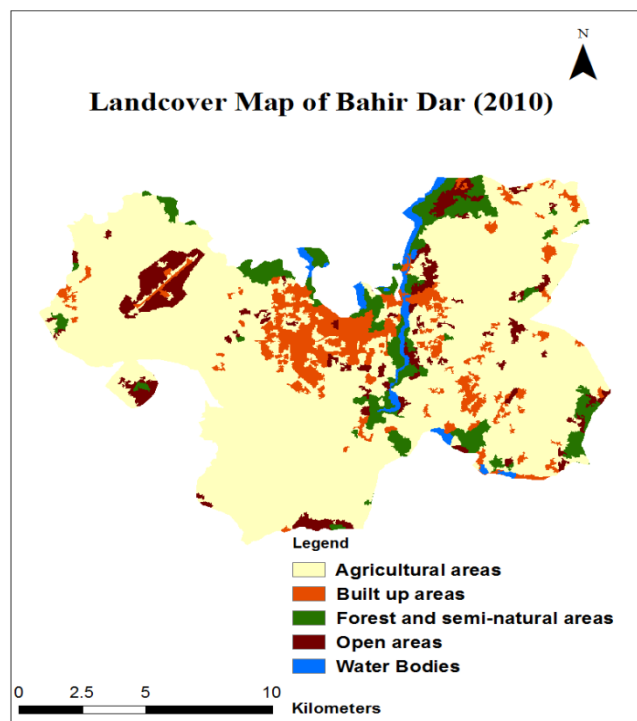
It is also visible from figure 4.1 and table 4.1 that water bodies have shown a decrease from 2.4% of the study area in 1986 to 1.6% in 2001 and again showed a little increase of about 1.7% of the study area in 2010. The small decreased in water bodies and changed to built up areas in 2001 was related to a retreat of the lake Tana and Blue Nile river due to siltation and the subsequent use of this land for built up areas. Haregeweyn et al (2006) had reported a similar study in other parts of Ethiopia and they showed that sediment delivered from agricultural watersheds threatened the life of both artificial and natural reservoirs. Moreover, Tana beles hydropower project has been built which reduces the water level during this time. In addition to this, the region is commonly known by geological basaltic



a) Map for 1986



b) Map for 2001



c) Map for 2010

Figure 4.1: Land cover map of Bahir Dar for 1986 (a), 2001 (b) and 2010 (c).

lava flow areas and mineral extraction and construction site which are found near to rivers that is why seen as built ups. The consideration of these construction sites was due to the nomenclature of classification described by CORINE (Kleeschulte and Büttner, 2006).

Open areas also showed a continuous increase within the distinct study periods as indicated in figures 4.1a, b and c above. Generally, agricultural areas and somehow built up areas were the most dominant land cover classes that has been observed in the study periods of 1986, 2001 and 2010. Table 4.1 below presents a summary of areas and percentage of land cover classes in the last 25 years.

Land cover classes	1986		2001		2010	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Built up areas	328.64	1.5%	869.51	4.1%	2011.54	9.4%
Water Bodies	520.65	2.4%	334.00	1.6%	368.68	1.7%
Forest and semi-natural areas	1146.00	5.4%	1459.53	6.8%	1578.85	7.4%
Open spaces	87.48	0.4%	369.98	1.7%	1438.25	6.7%
Agricultural areas	19261.45	90.2%	18311.20	85.8%	15946.90	74.7%
Total	21344.22	100%	21344.22	100%	21344.22	100%

Table 4.1: Area statistics of the land use and land cover units from 1986-2010

4.2. Accuracy Assessment of the Classification

Because classified land cover maps from remotely sensed images contain various types of errors, it is the responsibility of the researcher to find out those errors so as to make the produced land cover maps become reliable and easily interpretable by users. Once the classified image is integrated into a GIS, to become an information source for urban planners and researchers, accuracy assessment should be processed as it limits the classification results of a remotely sensed imagery data. To do so, the accuracy of a classified map has to be assessed and compared with a referenced data using an error matrix as explained in chapter 3 of section 3.2.4. The accuracy assessment in this study was made using the original mosaic image for 1986 and Google earth images for the study periods of 2001 and 2010.

4.2.1. User's Accuracy

Users accuracy refers to the number of correctly classified pixels in each class (category) divided by the total number of pixels that were classified in that category of the classified image (row total). It represents the probability that a pixel classified into a given category actually represents that category on the ground.

Results of user's accuracy in this study showed that in 1986 the maximum class accuracy was 98%, which was water bodies where correctly classified and the minimum was agricultural areas class with an accuracy of 80.6% as presented in table 4.2 below. In 2001, the class accuracies range from 62% to 100% where as in the period 2010, it ranges from 75% to 97.3% as indicated in tables 4.3 and 4.4 respectively. The lowest values of class accuracies were misclassified due to spectral property similarities among other land cover classes. As shown from tables 4.2, 4.3 and 4.4, the user's accuracy was lowest for agricultural areas as some of the agricultural areas were largely misclassified as built up, forest and semi-natural and open areas. Moreover, the time of image acquisition has a great role for such misclassification problems. Since the images obtained during the season where most agricultural activities were carried out in Ethiopia, other land cover classes appear as agriculture and vice versa. According to Václavík and Rogan (2009), the category of agriculture was the most problematic because it represented a mixture of various crops in different phenological stages as well as bare soil (plowed fields). In addition to this, the spatial resolution of Landsat data could have an influence on the image classification. According to Zhou et al (2009) for detailed urban land cover mapping at very fine scales, high spatial resolution imagery from satellite sensors such as IKONOS and QuickBird become more accurate.

4.2.2. Producer's Accuracy

Producer's accuracy refers to the number of correctly classified pixels in each class (category) divided by the total number of pixels in the reference data to be of that category (column total). This value represents how well reference pixels of the ground cover type

are classified. As showed in table 4.2, open areas were largely misclassified as 100% and in table 4.3, built up areas became a low accuracy of 66.7% where as agricultural areas had been largely misclassified as 100%. The lowest values for built up areas in table 4.2 and 4.3 were misclassified due to the similar spectral properties of different land cover classes such as open areas and agricultural areas.

Classified Map	Reference Map							
	Land cover classes	Built up areas	Water Bodies	Forest and semi-natural areas	Open areas	Agricultural areas	Grand total	User's Accuracy
	Built up areas	46	0	0	0	1	47	97.9%
	Water Bodies	0	49	1	0	0	50	98%
	Forest and semi-natural areas	1	0	39	0	0	40	97.5%
	Open areas	0	0	0	21	1	22	95.5%
	Agricultural areas	13	0	0	0	54	67	80.6%
	Grand total	60	49	40	21	56	226	
	Producer's accuracy	77%	100%	97.5%	100%	96.4%		
	Overall accuracy	92%						

Table 4.2: Confusion matrix for land cover map of 1986

Classified Map	Reference Map							
	Land cover classes	Built up areas	Water Bodies	Forest and semi-natural areas	Open areas	Agricultural areas	Grand total	User's Accuracy
	Built up areas	10	0	2	0	0	12	83.3%
	Water Bodies	0	21	0	0	0	21	100%
	Forest and semi-natural areas	0	1	20	0	0	21	95.2%
	Open areas	1	0	0	20	0	21	95.2%
	Agricultural areas	4	0	3	4	18	29	62%
	Grand total	15	22	25	24	18	104	
	Producer's accuracy	66.7%	95.5%	80%	83.3%	100%		
	Overall accuracy	86%						

Table 4.3: Confusion matrix for land cover map of 2001

Classified Map	Reference Map							
	Land cover classes	Built up areas	Water Bodies	Forest and semi-natural areas	Open areas	Agricultural areas	Grand total	User's Accuracy
	Built up areas	52	0	1	3	1	57	91.2%
	Water Bodies	0	38	2	0	0	40	95%
	Forest and semi-natural areas	0	1	37	0	0	38	97.3%
	Open areas	1	1	3	15	0	20	75%
	Agricultural areas	9	0	7	5	66	87	75.8%
	Grand total	62	40	50	23	67	242	
	Producer's accuracy	84%	95%	74%	65%	98.5%		
	Overall accuracy	86%						

Table 4.4: Confusion matrix for land cover map of 2010

4.2.3. Overall Accuracy

It is computed by dividing the total number of correctly classified pixels (i.e., the sum of the elements along the major diagonal) by the total number of reference pixels. It shows an overall results of the tabular error matrix. The overall accuracies performed in this study period 1986 was 92% (table 4.2), in 2001 was 86% (table 4.3) and during 2010 it was 86 % (table 4.4) as discussed in section 4.2.2. As mentioned by Anderson et al (1976) for a reliable land cover classification, the minimum overall accuracy value computed from an error matrix should be 85%. However, Foody (2002) showed that this baseline makes no sense to be a universal standard for accuracy under practical applications. This is because a universal standard is not exactly related to any specific study area. Foody (2002) also noted that Anderson et al (1976) do not explain in detail about the criteria of map evaluation for universal applications. Moreover, Lu et al (2004) noted that the accuracies of change detection results highly depend on many factors, such as: availability and quality of ground truth data, the complexity of landscape of the study area, the change detection methods or algorithms used as well as classification and change detection schemes. So, the overall accuracies for both maps were above 85% based on Anderson's criteria.

4.3. Land cover changes of Built up areas

The increment in infrastructure development of Bahir Dar from time to time has played a major influence for the expansion of built up areas. The main focus of this study was assessing and examining the spatial extents of built up areas within the three study periods. To achieve this, a reclassification was made to generate land use and land cover maps of built up and non built up areas as shown in figure 4.2 below. As clearly seen in table 4.5, the proportion of built up areas in 1986 was 1.54% of the entire study area. In 2001 the percentage of built up areas showed more than double increase and it was 4.07 % and in 2010 it reached to 9.42% of area coverage.

Landcover class	1986		2001		2010	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Built up areas	328.64	1.54	869.51	4.07	2011.54	9.42
Non Built up areas	21015.58	98.46	20474.71	95.92	19332.68	90.57
Total (ha)	21344.22	100	21344.22	100	21344.22	100

Table 4.5: Built and non built-up areas between 1986 - 2010

The study area has experienced spatial increase of different land use and land cover classes such as; built up areas, due to the corresponding horizontal expansion as well as conversion of land cover classes during the distinct study periods. The reclassified images in figure 4.2 showed that there had been a rapid land cover change from non built up areas to built up areas. In both study periods, agricultural areas were the most dynamic classes which contributed to the increase of built up areas. There was a huge decrease of built up areas from 1986 to 2001. This was related to the destruction of built up areas such as; factories, small urban centers, military and air force camps due to the war between the former socialist regime and the opposition army during 1989 - 1991. Moreover, a resettlement policy was takes place throughout the country in 1989 and 1990 for land management as well as to provide better infrastructure facility. Following this a lot of built up areas were converted to agriculture and open areas as shown in figure 4.1 and figure 4.2.

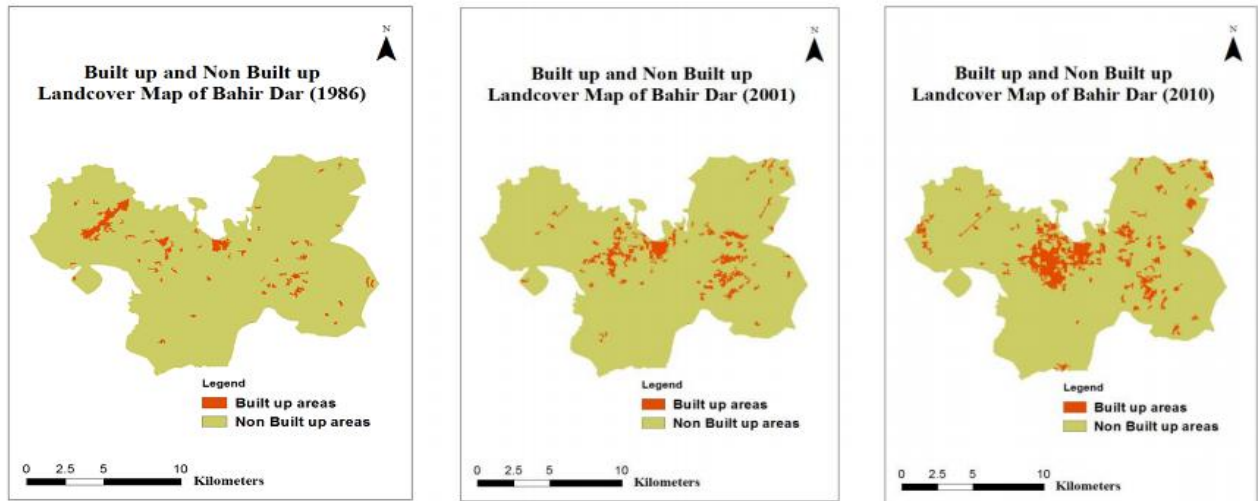


Figure 4.2: Built up and Non built up areas for 1986 (left), 2001 (middle) and 2010 (right) respectively.

4.4. Analysis of Land cover maps using LCM

In this study the classified land cover maps of 1986, 2001 and 2010 were used as input parameters and LCM was applied to identify the locations and magnitude of the major land use and land cover changes and persistence. Moreover, the spatial trends of major transitions between land use and land cover categories of special interest in the study area has been quantified.

4.4.1. Change Analysis Results of LCM

The results of the cross-tabulation comparison of both land use and land cover maps in figure 4.3 below showed that there have been marked changes in all land use and land cover classes between 1986, 2001 and 2010. During the period 1986 - 2001 the total built up areas increased by 711 ha (representing an increase of 2% of the total study area) and lost 170 ha (0.45 % of the study area) as indicated in figure 4.3 a. While agricultural areas decreased by 1499 ha (4% of the total study area) and gained 549 ha with a net loss of 950 ha. Similarly water bodies lost 225 ha and gained 38 ha. The proportion of areas covered with forests and semi-natural areas increased by 659 ha, while the proportion of open spaces increased by 355 ha. The increase in forest and semi-natural areas in both study periods has been associated to an increasing trend of plantation of eucalyptus tree in the

Koga catchment and near to water bodies. This is because farmers in the area harvested eucalyptus tree as a good source of income instead of farming crops which was a challenge in the cost of fertilizers.

The built up areas have also continued to increase with a gain of 1441 ha in the period 2001-2010 shown in figure 4.3b. Similarly the consistent decrease of agricultural areas have been also seen in this time with a loss of 2892 ha. From figure 4.3 c, the overall changes occurred for the last 25 years in built up areas have shown an increase of 1836 ha gain (representing an increase of 5% of the total study area) with a loss of 165 ha (0.44 % of the study areas). Whereas agricultural areas have lost 3766 ha (10% of the study area) and gained only about 473 ha or 1.25% of the study area.

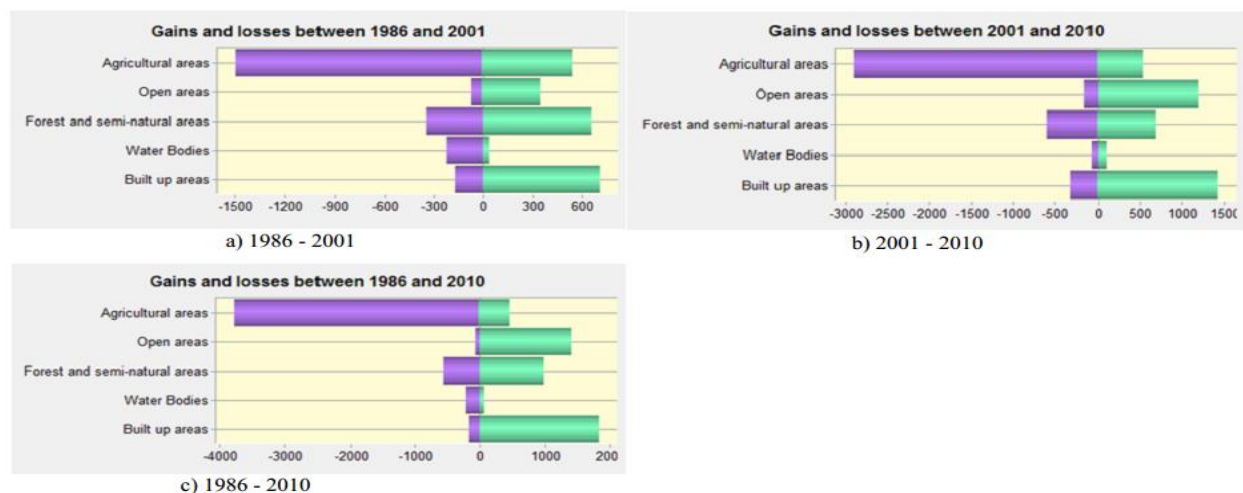


Figure 4.3: Gains and losses of land cover classes in (ha).

The land cover changes between the study periods were quantified by using differences from the late periods to early study periods. Table 4.6 below shows the changes that has been seen in the past three distinct study years quantified through LCM. Built-up areas showed a big change of 5.3% between 2001 -2010 rather than 1986-2001 with only 2.6% which was a 16 years period. Following this, there has been a great loss of agricultural land from 950 ha in 1986-2001 to 2364 ha in 2001-2010 which contributed to an increase in the changes of built up areas, forest and semi-natural areas and open spaces as shown in table

4.6 below. The slight increase in the category of water bodies (0.1%) in 2001-2010 shown in figure 4.3b and table 4.6 could be related to the construction of the Koga dam and reservoir in the periphery of the study area.

Land cover classes	1986 - 2001		2001-2010		1986 - 2010	
	Area change in (ha)	%	Area change in (ha)	%	Area change in (ha)	%
Built up areas	541	2.6	1142	5.3	1683	8
Water Bodies	-187	-0.8	35	0.1	-152	-1
Forest and semi-natural areas	314	1.4	119	0.6	433	2
Open areas	283	1.3	1068	5.0	1351	6
Agricultural areas	-950	-4.4	-2364	-11.1	-3315	-16

Table 4.6: Comparison of changes in land cover classes between 1986-2010 using LCM.

The contributions of other categories to their net change is presented in figure 4.4 below. It has been clearly shown that agricultural areas explained the majority of the total increase in

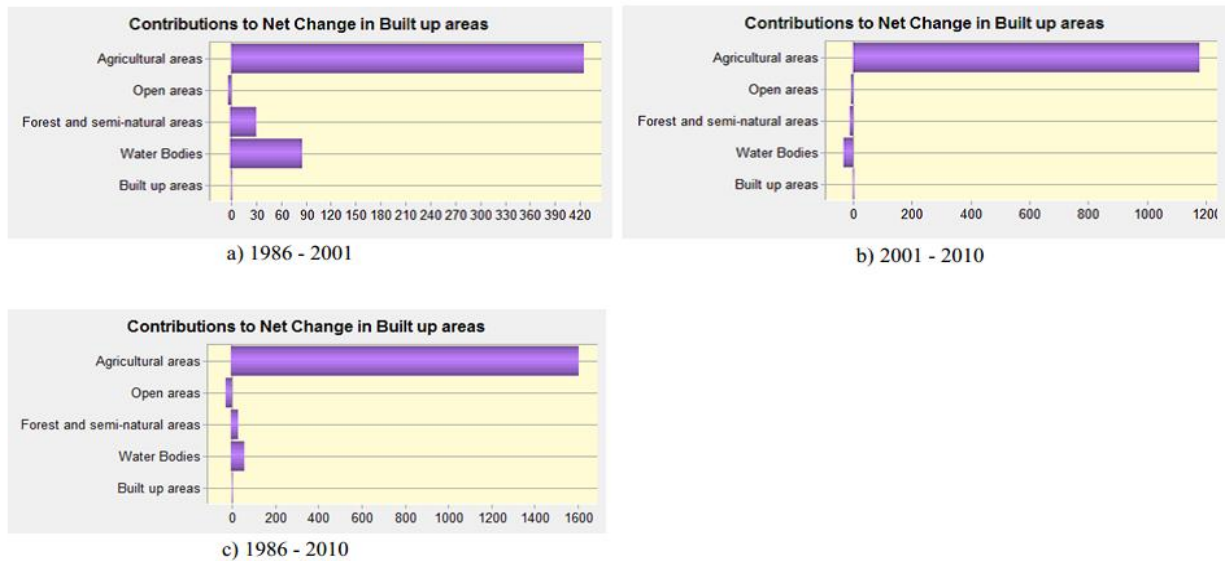


Figure 4.4: Contributions of land cover classes to built up areas in (ha).

built up areas (425 ha), which represents about 1.12% of the entire study area in 1986-2001 as indicated in figure 4.4a. Next to agricultural areas, water bodies take the second contribution to total increase in built up areas by about 88 ha (0.23% of the study area). As

indicated in figure 4.4b and c, agricultural areas were also continued contributing a majority of about 1178 ha and 1609 ha which means that 3.12% and 4.26% of the entire study area respectively.

A more simplified cross-classification map is presented in appendix A (figure A.1) section of which indicates persistence in land use and land cover categories, i.e., areas where no change occurred, losses and gains. Areas with some transitions between land use and land cover classes were depicted as red and green. And areas with no changes between study periods were indicated as yellow (for persistence). Based on this map, built up areas has gained about 711 ha and loss 170 ha as quantified in figure 4.3 a. In general, built up areas has showed expansions from 1986 to 2001 and 2001 to 2010 in almost all direction of the entire study area according to appendix A (figure A.1).

4.4.2. Transition of Land cover Classes

LCM allows to produce and evaluate transitions from one landcover state to another both in map and graphical form. In this study, a transition map was generated from all landcover classes to builtup areas in order to visualize and interpret the changes happened between 1986 and 2010. Because the main focus of this study was on built up areas, the transition has been made to this specific landcover class (built up areas). Agricultural areas showed the majority of increased transitions between 1986-2010 as shown in appendix A (figure A.2) and water bodies followed at second level to this transition. These transitions could be viewed as possible development and caused by socio-ecological feedbacks that arise from socio-economic changes.

4.4.3. Spatial Trend of Change

The spatial trend analysis tool in LCM was used to compute maps of transition trends from all land cover categories to built up areas between 1986 to 2010. It was created using a default 3rd order of polynomial, which is best fit to the pattern of change, in LCM. The numeric values produced don't have any special significances (Eastman, 2012). Thus, the

result is interpreted as: the lower the value, the less changes and the higher the value, the more changes. The resulting map is presented in figure 4.5 below which provides a means of generalizing transition trends of built up areas for easy interpreting complex land change patterns. From figure 4.5 it is evident that the transition intensity of built up areas was more intense in the center of the study area. The trend has shown a growing (sprawling) of built up areas towards the west and somehow towards south relative to other directions. Thus, the trend and extent of changes in built up areas are likely to continue with the rapid development of infrastructure, tourism economy and increasing of population.

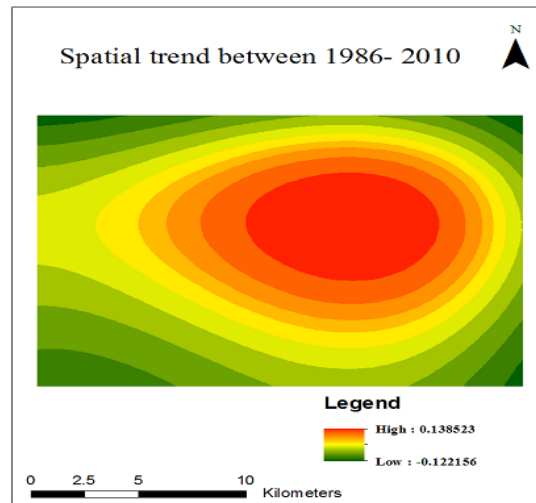


Figure 4.5: Map of spatial trend of changes in built up areas between 1986- 2010.

From the transition point of land cover classes in the change analysis process, it has been resulted a number of transition of land cover classes. Agricultural areas have showed the majority of these transitions between 1986-2001 as shown in appendix A (figure A.2). Moreover, water bodies also expalied by a major transition next to agricultural areas. These transitions could be viewed as possible development and caused by socio-ecological feedbacks that arise from socio-economic changes.

As briefly discussed in chapter 3 of section 3.3.2.1, major transitions occurred between 1986 - 2001 were selected for modeling process to create the transition potential maps for further prediction. The explanatory power result for the variables (factors) created to

explain urban expansion have shown acceptable value. Dynamic variables such as distance to major roads and distance from built up areas (map 1986) have scored values of 0.18 and 0.17 respectively. However, slope and distance to major rivers had a value of 0.03 and 0.09 respectively.

Since this study was based on an integration of MLP and Markov chain model, the MLP in LCM has been run to create transition potential maps with multiple transitions. To do so, an automatic selection of 1067 cells were chosen by MLP for transitions from 1986 to 2001 to be modeled. The MLP has finished 10,000 iteration (default) training and testing with an accuracy of 61%. The computed accuracy was lower than what most literatures said. However, Islam and Ahmed (2011) reported an accuracy of 57% for land use prediction as a good value and depends on factors used in a specific study. The influencing variables incorporated in this modeling process such as slope and distance to major rivers had lower values of Cramer's V. Therefore, the lower accuracy of MLP run was due to these low power of affecting variables, but still it is satisfactory to run it. After this, the potential maps were generated as indicated in appendix A (figure A.3). After the transition potential maps were created through MLP, the model was ready to predict the changes using Markov chain analysis for future date (in this case for 2010). The simulated land cover map was then generated.

4.5. Model Simulations and Validations

Results from Markov chain model simulations are based on a transition probability matrix of landuse changes from time-1(1986) to time-2 (2001) due to historical changes. This has become the basis for projection to an other time period (2010). Figures 4.6a and 4.6b indicated the actual and simulated land cover maps of Bahir Dar for the year 2010 respectively which showed visible differences. This had been expected as the historical change processes from 1986 to 2001 cannot be the same as from 2001 to 2010 in Markov chain analysis. In addition, constraints and driver variables (factors) created for defining the rules highly affected the simulation results as they are sensitive to small changes.

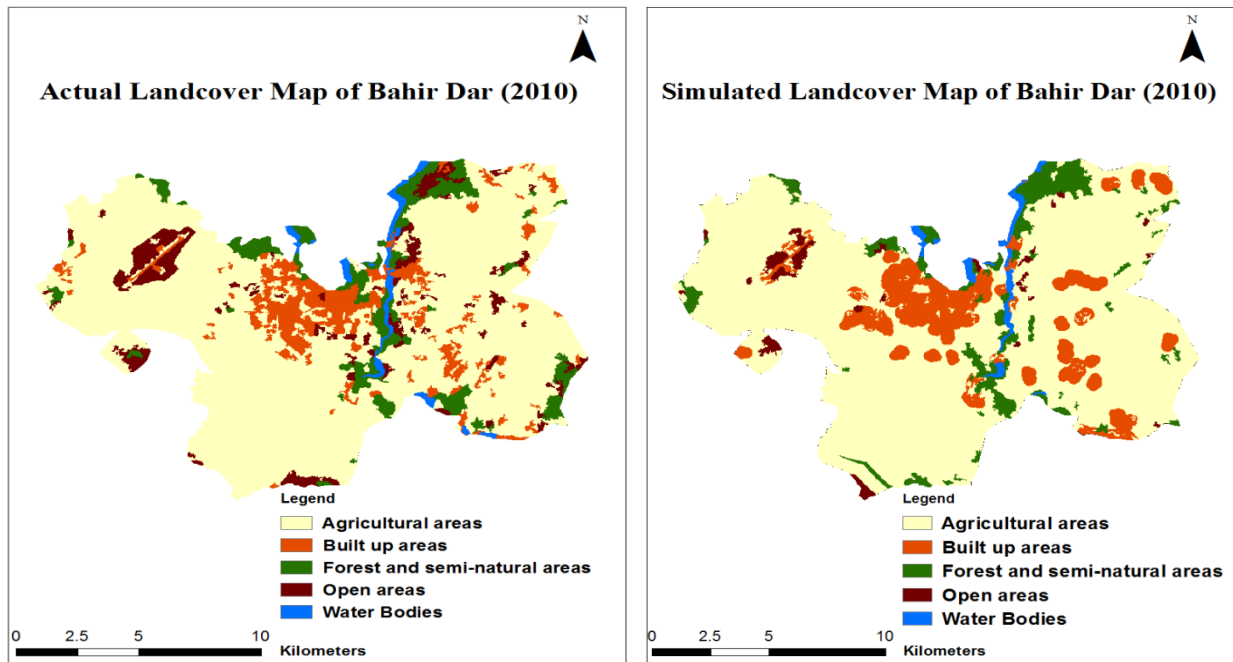


Figure 4.6: Land cover maps for 2010 actual (left) and simulated (right)

As shown in figure 4.6b, much of agricultural areas have been converted in to built up areas. However, the model missed much of open areas and overestimated some how forest and semi-natural areas as compared to the actual map shown in figure 4.6a. Although there had been much expansion of built up areas, however, the conversion between other landcover classes was limited. This has been related to the power of driving variables incorporated in the transition sub model where the accuracy of MLP and Markov chain highly depend on.

For validation, the model's out put is compared to a map of land use prediction with actual land use map of 2010. Thus, a three map comparison is required with two reference times and a simulated time. In this case the land cover maps considered were reference time 1 (2001), reference time 2 (2010) and the simulated map (2010). This helped to observe the changes between the years 2001, 2010 and to compare with the simulated map (2010) to distinguish whether the changes have been predicted correctly or not. Fig 4.7 below was created for showing a comparison of observed changes with predicted changes which identified four types of correctness and error which are; correct due to observed persistence

predicted as persistence (null successes), correct due to observed change predicted as change (hits), error due to observed persistence predicted as change (false alarms) and error due to observed change predicted as persistence (misses) (Martins et al, 2012).

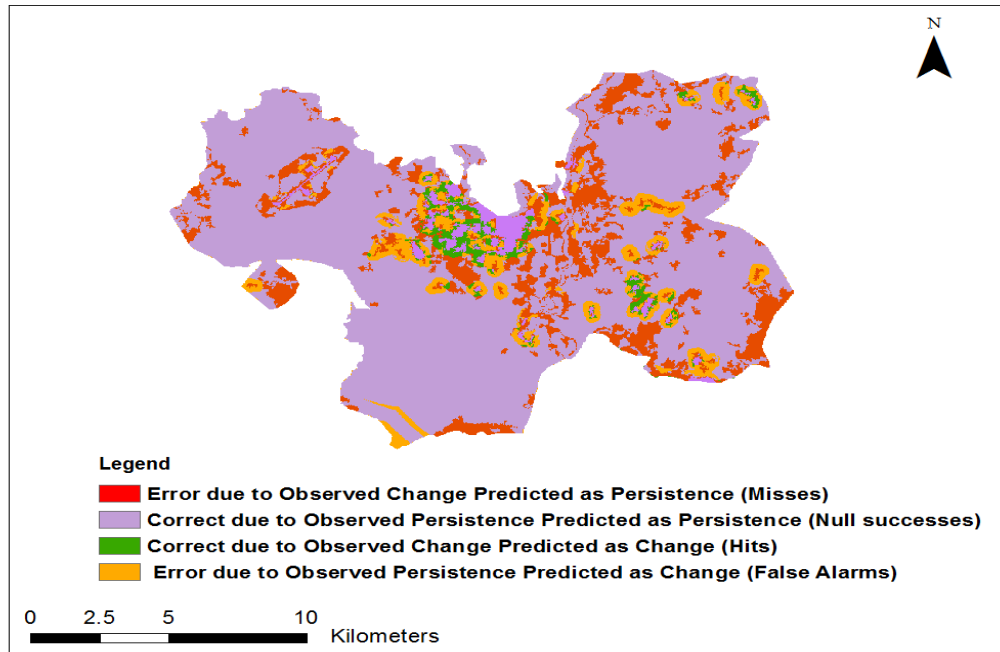


Figure 4.7: Prediction correctness and error map based on land cover maps of 2001 (reference), 2010 (reference) and 2010 (simulated)

The accuracy of the model has been illustrated by the output image of figure 4.7 above where it computed and specified both hits, misses and false alarms. It was visible from figure 4.7 that the overall distribution of hits (predicted changes correctly) were lower than false alarms and misses. The area correctly predicted (hits) by the model (LCM) was only 2.8% of this study area which is a lower performance. Therefore, the accuracy of the model is lower in predicting changes (hits) in this specific study area. The reason for this lower performance is that the weak power of influencing variables responsible for urban growth. In addition, the length of time periods between the land cover maps should have been be uniform. This is one of the requirements of Markov chain analysis, however, especially in case of land use applications this is difficult to manage due to uneven temporal availability

of satellite data. So in this study there was a 15 year gap between the first two image acquisitions, however, due to unavailability of imagery data of similar period, the gap between the last two images was only 9 years. From this point it is evident that simulation results could have limitations as changes between 1986 -2001 and 2001 -2010 may not proceeded in similar pattern.

Pontius and Millones (2011) and Martins et al (2012) proposed disagreements in quantity and allocation parameters for validating the accuracy of model performance. Where quantity disagreement is the amount of difference between the reference map and a comparison map that is due to the less than perfect match in the proportions of the categories. Whereas allocation disagreement as the amount of difference between the reference and comparison map that is due to the less than optimal match in the spatial allocation of the categories.

Based on the above proposed suggestions, a cross-tabulation matrix was computed by comparing the actual and simulated land use map of 2010 as shown in table 4.7 below. The total disagreement (quantity + allocation) resulted in this study was 13% which showed a visible difference between the reference and comparison map. Disagreement value ranges from 0 to 1 where a disagreement of equal to 0 means the two maps agree whereas a positive value, however, show differences in quantity and allocation between the reference and comparison (simulated) maps of 2010. Thus, in this study the model (LCM) has shown a lower performance with an error of 13% disagreement which is greater than the correctly predicted values (hits = 2.8%) for specifying the correct quantity and allocation of each category.

Classification agreement/disagreement	Values in (%)
Chance agreement	17
Quantity agreement	21
Allocation agreement	49
Allocation disagreement	10
Quantity disagreement	3

Table 4.7: A summary of derived accuracies of the model

The components of agreement specify distinct characteristics in which the comparison map agrees with the reference map (Estman, 2012). Chance agreement is the agreement that a scientist could achieve with no information of location and no information of quantity. Quantity agreement is the agreement when the comparison map is somewhat accurate in terms of its specification of quantity of each category. Whereas allocation agreement is the agreement when the comparison map is somewhat accurate in terms of its specification of the location of each category (Pontius, 2002). Agreement value ranges from 0, meaning no overlap to 1, meaning perfect agreement between observed and predicted changes.

Therefore, agreement between the reference and simulated maps was evaluated based on quantity and allocation agreements. From table 4.7, the model has shown a quantity agreement of only 21% in specifying of each category and an allocation agreement of 49% in terms of specifying the location of each category. Thus, in both cases (quantity and allocation agreements) the model had performed a lower accuracy in simulating changes and specifying the correct quantity and allocation of each category in this study area.

As it was explained in section 3.2, flow chart in figure 3.2, prediction of land cover map for 2020 was designed. But in section 3.3.3, an assumption was set for modeling for the year 2020 in such a way that if the accuracy of the model was acceptable, future prediction would be done. After validation results, however, the model achieved a lower and unacceptable accuracy. Therefore, modeling of land use and land cover changes in Bahir Dar for 2020 could not possible.

Generally, land use change modeling with LCM has provided and quantified rapid changes and spatial trends of land use and land cover changes in Bahir Dar area for the distinct study periods. However, the model (LCM) showed a lower accuracy in simulating changes. This could be due to inadequate explanatory variables and their changes over time in modeling processes, image classification errors and the shape of the contiguity filter used.

CHAPTER FIVE

5. CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

Land use and land cover changes have wide range of consequences at all spatial and temporal scales. Because of these effects and influences it has become one of the major problems for environmental change as well as natural resource management. Identifying the complex interaction between changes and its drivers over space and time is important to predict future developments, set decision making mechanisms and construct alternative scenarios.

This study has been conducted by integrating GIS, remote sensing and spatial modeling tools. In order to detect and analyze changes in land cover classes, these techniques were implemented. In the first section, satellite data for the study periods of 1986, 2001 and 2010 and remote sensing techniques were applied to generate land cover maps through a maximum likelihood supervised image classification algorithm. The accuracy assessment and change detection processes has also been done. The overall accuracy of land use and land cover maps generated in this study had got an acceptable value of above the minimum threshold. The information from image classification accuracy became important to the modeling procedure. In the last section, land use modeling was applied to analyze dynamic changes in built up areas as a result of different driving factors.

From the remote sensing of image classification result, the study showed that the proportion of built up areas were increased. There was a rapidly changing of built up areas from 1.5% in 1986 to 4.1% in 2001 and 9.4% in 2010. Agricultural areas were played a major role for this much conversion to built up areas. It showed a continuous decreasing from 90.2% in 1986 to 85.8% in 2001 and finally had a value of 74.7% in 2010. The conversion of agricultural land to built up areas could be related to increment of population and faster economic development in Bahir Dar area. Accuracy assessments of classified

images show better results with an overall accuracy of 92% in 1986, 86% in 2001 and 86% in 2010.

The change analysis results from LCM also showed that built up areas gained 711 ha between 1986-2001 and 1441ha between 2001-2010 where as agricultural areas lost with a total of 1499 ha and 2892 ha respectively. The contribution of land cover classes to the increase of built-up areas also showed that agricultural areas explained the majority of the total increase by 425 ha, 1178 ha and 1609 ha for 1986-2001, 2001-2010 and 1986-2010 respectively. The spatial trend of changes in built up areas between 1986-2010 were assessed through transition from all categories to built up areas in LCM. And it indicated that there was a growing pattern to the western part of the study area with a small trend towards south relative to other directions. The trend and extent of changes in built up areas are likely to continue with the rapid development of infrastructure, tourism economy and increasing of population as discussed in the result section in chapter 4.

Land use change models such as LCM provided an important spatio-temporal information of land use and land cover changes especially on urban areas. It also provide the possibility to understand the influence of urban dynamics supported by a set of drivers. Model results have shown remarkable changes in built up areas between the study periods. The accuracy of MLP to generate transition potential maps has got an acceptable value of 61%. Simulated results of 2010 quantified that much of agricultural land had been converted in to built up areas regardless of the driving factors which have negative impacts on the simulation process. Although the accuracy of MLP was good to model transition potential maps, simulated results using Markov chain showed visible differences with the actual land cover map of 2010. Validation results based on total disagreements (quantity and allocation disagreement) showed that the model, LCM, performed a total disagreement of 13% and considered as a lower performance. Validation using a three map comparison also confirmed that LCM showed a lower accuracy in predicting land use changes (hits) correctly in this study area (Bahir Dar area).

5.2. Recommendations

The results of this specific study have shown that remote sensing, GIS and land use models are important tools in land use and land cover change studies. Therefore, based on the findings of this study, the following are recommended as future research directions:

- The use of high resolution imageries such as IKONOS and QuickBird are important in generating good quality of land cover maps. Because urban areas have complex and heterogonous features, a high resolution imagery provide better information by mapping these areas. Moreover, the use of ancillary data as ground truth helps for better accuracy of an image classification.
- Consistent multi-temporal Landsat satellite data for each year provides detail comparison of images, change analysis and modeling. Especially for Markov chain model, it is a requirement of equal interval of images acquisition although there have been uneven temporal availability of data.
- Incorporating socio-economic data, land policy, biophysical and human factors (population density, technology, political) could improve the performance of land use models for future predictions. Hence, it is important to the planners, decision makers and stakeholders for efficient utilization of land.

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APPENDICES

Appendix A

Figures

Cross tabulation maps of gains and losses, transition of land cover classes, transition potential maps and trends of maps.

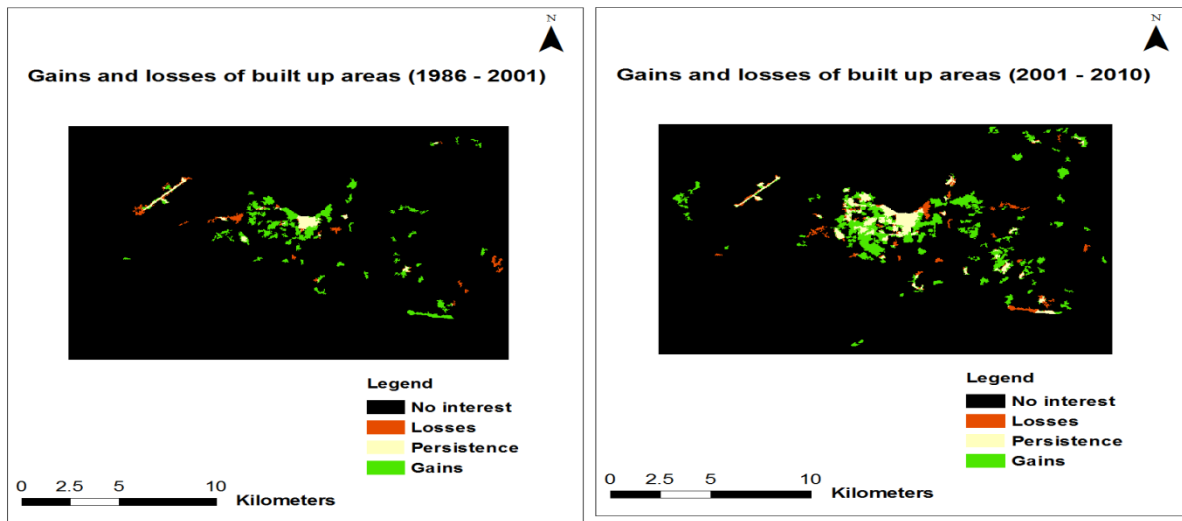


Figure A.1: Gains and losses of built up areas 1986 -2001, (left) and 2001-2010, (right).

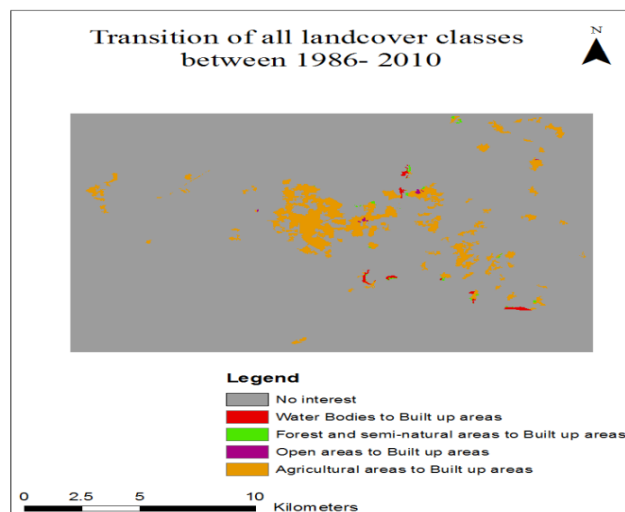


Figure A.2: Transition of all landcover classes to built up areas in 1986 -2010.

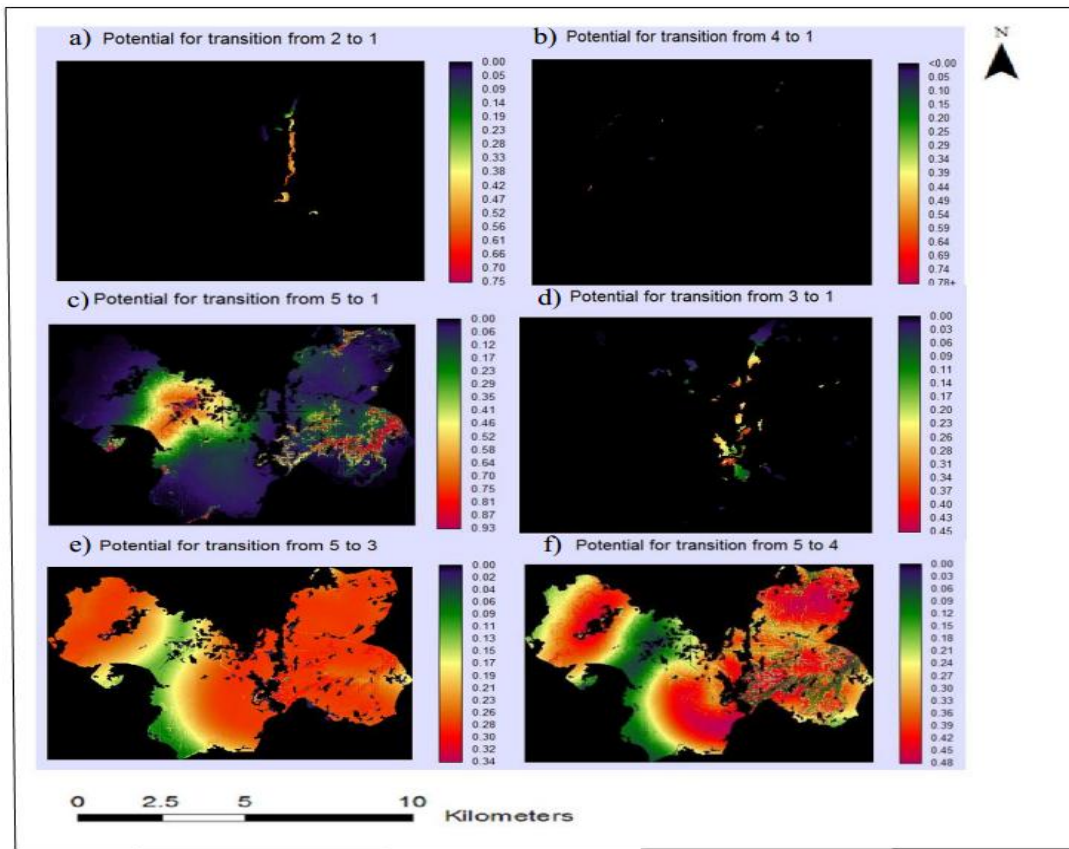


Figure A.3: Transition potential maps a) Water bodies to built up areas, b) Open areas to built up areas, c) Agriculture to built up areas, d) Forest and semi-natural areas to built up areas, e) Agriculture to forest and semi-natural areas and f) Agriculture to open areas

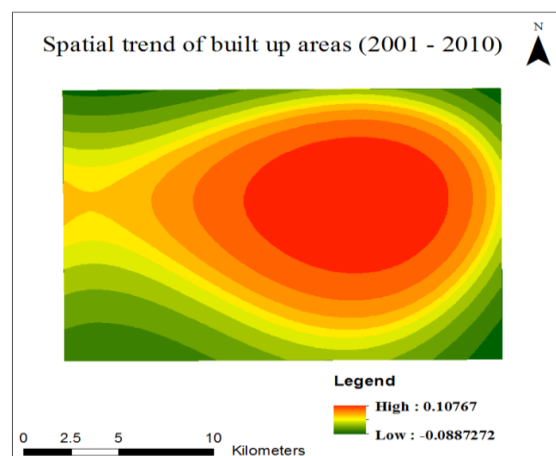


Figure A.4: Map of spatial trend from all to built up areas between 2001- 2010.

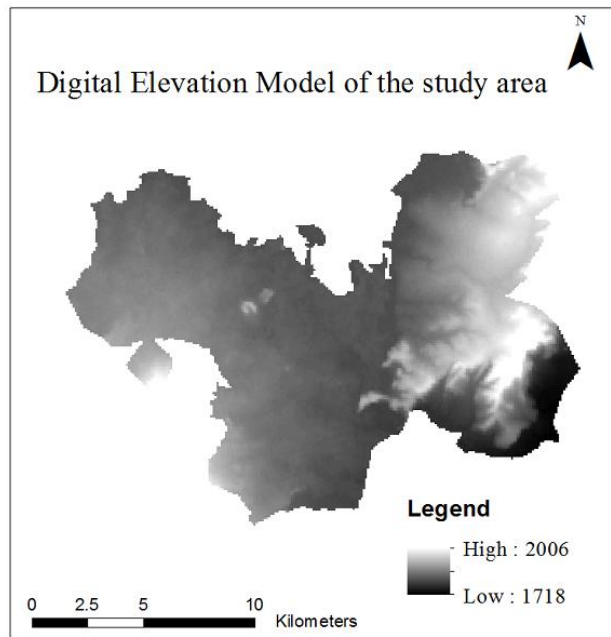


Figure A.5: Digital elevation model of Bahir Dar.

Appendix B

Tables

Cross tabulation performs a cross-tabulation analysis that compares images containing categorical variables of two types. The table below was computed from actual land cover map of 2010 and simulate map of 2010.

Classified Map	Land cover classes	Built up areas	Water Bodies	Forest and semi-natural areas	Open areas	Agricultural areas	Grand total
	Built up areas	12811	478	1240	1394	17281	33204
	Water Bodies	76	3205	609	92	64	4046
	Forest and semi-natural areas	504	562	10610	3043	3691	18410
	Open areas	225	0	475	10300	1635	12635
	Agricultural areas	10999	235	6404	2778	173609	194025
	Grand total	24615	4480	19338	17607	196280	262320

Table B.1: Cross tabulation of actual land use and land cover 2010 (columns) against simulated land use 2010 (rows)